EMPIRICAL ESSAYS ON SCHOOL CHOICE AND HUMAN CAPITAL INVESTMENTS

by

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Abstract

This dissertation explores individuals' investment in human capital and how that interacts with public policy interventions. I focus on two forms of investment in human capital: investments in skills and health. First, I focus on parents' investment in children and parental labor supply and asset accumulation decisions as they interact with private schooling. Second, I investigate whether individuals rely on outside sources of information, such as expert reviews and word-of-mouth, when making investments in their health.

In the first chapter, "Dynamic Female Labor Supply, Investment in Children and Private Schooling", I explore how the private schooling investment decision for the child affects maternal labor supply and savings over the life cycle. Women with children face a well-known trade-off between working, which allows greater monetary investments in children, and spending more time with the child. I build and estimates a dynamic model of female labor supply to investigate how the option of private schooling affects this trade-off. The model extends existing work on female labor supply and children by incorporating private versus public schooling choice, allowing for risk aversion and savings, and nesting within the model a child ability production function. Results of the structural estimation show that mother's time with the child and private schooling are complements, and that the availability of private schooling leads to more work and more saving among less educated women. However, more educated women drop out of the labor force and increase the time they spend with their child when the child is going to private elementary school. In addition, I estimate the price elasticity of private school enrollment to be -0.25. Policy simulations show that targeted private school subsidies to low income and less educated mothers can reduce inequality in children's outcomes. Moreover, by inducing women to increase their labor supply to be able to top up subsidies and send their children to private schools, targeted subsidies can help women at the margin accumulate higher assets and experience wage growth of up to 20 percent over the life cycle.

The second chapter of the dissertation, titled "Housing Demand and Private Schooling ", studies the effect of house price increases on the choice to enroll children in private schools. I exploit cross-city variation in local housing booms during the 2000s, which increased net worth of households and allowed them to borrow using home equity lines of credit. To establish a causal relationship between the housing boom and the demand for private schooling, I employ instrumental variables techniques used in the literature studying the effects of the house price boom on different facets of the economy. Results show that a one standard deviation larger increase in local housing demand shock of 2000-2006 increased average private school enrollment by 18%. However, this increase was counteracted by an equal decline in private school enrollment during the subsequent housing bust starting in 2007. This indicates that changes in parental income can have significant effects on the choice of schooling and that the housing boom of 2000s can potentially have lasting positive effects on the human capital of the next generation.

In the third chapter, “Positively Aware? Conflicting Expert Reviews and Demand for Medical Treatment”, which is joint work with Nicholas Papageorge and Jorge Balat, we study the impact of expert reviews on the demand for HIV treatments. Reviews are provided by both a doctor and an activist in the HIV lifestyle magazine Positively Aware, which we merge with detailed panel data on HIV-positive men’s treatment consumption and health outcomes. To establish a causal relationship between reviews and demand, we exploit the arrival of new drugs over time, which provides arguably random variation in reviews of existing drugs. We find that when doctors and activists agree, more positive reviews increase demand for HIV drugs. However, doctors and activists frequently disagree, most often over treatments that are effective but have harsh side effects, in which case they are given low ratings by the activist but not by the doctor. In such cases, relatively healthy consumers favor drugs with higher activist reviews, thus defying the doctor, which is consistent with a distaste for side effects. This pattern reverses for individuals who are in worse health and thus face stronger incentives to choose more effective medication despite side effects. Findings suggest that consumers demand information from experts according to the trade-offs they face when making health investments in the presence of adverse treatment side effects.

Primary Reader: Robert A. Moffitt

Secondary Reader: Nicholas W. Papageorge

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Dedication

This thesis is dedicated to my grandparents.

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Chapter 1

Dynamic Female Labor Supply, Investment in Children and Private Schooling

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This research was conducted with restricted access to Bureau of Labor Statistics (BLS) data. The views expressed here do not necessarily reflect the views of the BLS.

1.1 Introduction

An extensive literature in economics recognizes the importance of early childhood investments, including schooling, parental time and other goods, in the development of cognitive and non-cognitive skills.[1] One such investment is private schooling. Roughly 11% of all students in the United States (or about 5.4 million children) attend private school, and much research has examined its impacts, showing positive returns for students along a number of dimensions.[2] However, private schooling is expensive. While research has focussed on showing considerable returns to private school, the literature is silent on the fact that it must be paid for. Given the magnitude of costs (between $5,000 to $40,000 per annum), the private school investment may lead to shifts in labor supply and savings of parents, particularly mothers, both during private school, but even before, including prior to a child's birth. Seen this way, the private schooling decision constitutes an important additional dimension to the typical time investment trade-off that mothers face. In particular, mothers must choose between time investments versus working to afford private schooling investments in an effort to develop their children's skills. More broadly, adding this dimension to the mother's decision illustrates how policies affecting the provision of schooling can have impacts not only on children but also on the economic behavior of mothers, even before children are born.

[1] See [1, 2, 3, 4, 5, 6, 7]

[2] See [8] for a comprehensive summary of the literature on the effects of private schooling on child outcomes.

CHAPTER 1. DYNAMIC FEMALE LABOR SUPPLY, INVESTMENT IN CHILDREN AND PRIVATE SCHOOLING

In this paper, I build and estimate a dynamic model of female labor supply, savings and child's schooling decision to study the role of private schooling in shaping women's career path and asset accumulation. The effect of private schooling on female labor supply is theoretically ambiguous and depends on the interaction between woman's observed characteristics such as education and household resources, her unobserved characteristics such as preferences and productivity at home and in the labor market, and the cost of private schooling. To empirically investigate this theoretical ambiguity, the structural model captures the following key features. First, it incorporates private schooling choice for the child into a framework linking child-related costs to female's career trajectories ([9, 10, 11, 12, 13, 14, 15]). By incorporating private schooling into the mother's decision problem, I explicitly account for the trade-off between working to afford high tuition and spending time with the child, that also increases child ability. Second, the model incorporates risk-aversion and savings to capture how forward-looking mothers can plan for child's schooling in advance and smooth their consumption after childbirth when the value of mothers' time at home is higher. Third, the structural model characterizes selection by allowing for permanent unobserved heterogeneity to affect child's schooling choice as well as all the endogenous decisions in the model.

In studying how female labor supply links to private schooling, this paper contributes to two main literatures. The first one is on parental investment and child development [16, 17, 18, 19, 20, 21, 22].[3] One area receiving considerable attention is daycare for the child. The literature has generally found negative effects on child development of mothers increasing their labor supply [23, 24, 25, 26, 27]. This effect presumably arises because of low quality child care outweighing any reductions in maternal time investments but increases in goods investments. However, the existing analysis leaves out a critical dimension of investment in children: the quality of monetary investments. I add to this literature in two significant ways. First, I add private schooling choice for the child in the mother's optimization problem, which allows me to examine the role of different qualities of investments. Second, I cast this decision in a dynamic setting which endogenizes female's time allocation choice, human capital accumulation, wages and savings decision. The setting allows me to quantify the career costs of children for mothers who make different choices for their child's schooling, and study how preference for private schooling for children manifests itself in women's work decisions even before the child starts school.

Second, this paper contributes to the literature on the returns to private schooling, which finds that private schooling increases the probability of graduating high school and attending college as well as improve test scores and non-cognitive outcomes [28,

[3] [16] and [17] are the seminal papers this literature, in which parents can affect child ability through monetary and time investments. More recent papers jointly estimate parent's time allocation decision and child ability production function to address the endogeneity of inputs in child ability. Joint estimation of mother's time allocation decision and child ability production function alleviates concerns about the endogeneity of the work decision. The endogeneity can arise due to two reasons: (1) women who work more may be systematically different from those who do not work, which may be correlated with the ability of the child, and (2) mother's work decision may depend on the child's ability itself, in that mothers may compensate a "low ability" child by spending more time with him, or she may choose to spend more time with a "high ability" child for reinforcement of skills.

29, 30, 31, 32, 33, 34, 35]. These studies only look at the ceteris paribus impact of private schooling. However, the impact of private schooling does not occur in isolation. The cost associated with private schooling can affect parental behavior and other investments. I add to this literature by linking private schooling choice for the child with the mother's optimization problem. This allows me to capture the mechanisms through which private schooling can positively affect child ability, taking into account not just the direct impact of schooling but also the effect on investments working through women's work choices and asset accumulation. This also means I can tie schooling policies to female decisions even before a child is born. In particular, the private schooling choice for children can affect mothers' work decisions even before the child starts school, which will in turn affect monetary and time investments that mothers make in their children. Moreover, I am able to capture possible complementarities between inputs into the child ability production function, that can help explain why some children gain more from private schooling than others.[4]

I begin my analysis by presenting descriptive results on who sorts into private schools, and how the labor supply of women who send their children to private school differs from public school mothers over the life cycle. Using data from the National Longitudinal Survey of Youth 1979 (NLSY79) and NLSY79 Child and Young Adult

[4]This paper also adds to the literature on schooling and household decisions, which is not well-developed, though a few papers look at housing choices and school quality, showing that school quality affects household decisions in profound ways [36]. In a companion paper, I find that an increase in parents' wealth due to increases in house prices leads to a 22% increase in children's private school enrollment [37].

Survey, I show that more educated and high-income women are more likely to choose private schooling for their children. Additionally, I find that before childbirth, women who eventually select private schooling for their children work more, both at the extensive and the intensive margin, compared to public school mothers. However, this gap reverses after childbirth. Moreover, there is considerable heterogeneity across education and income groups in how private schooling interacts with labor supply. In particular, private school mothers with less education and lower levels of non-labor income work more than public school mothers throughout the child's life cycle. On the other hand, women with higher education and non-labor income who send their child to private school work substantially less than public school mothers of similar education and income after childbirth.

These data patterns motivate the specification of the dynamic structural model. The results of the structural estimation show that mother's time with the child and private schooling are complements, and that mother's time is most productive when the child is less than six years of age. The availability of private schooling leads to less educated women working more to afford private schooling for their children. However, due to the complementarity between private schooling and mother's time with the child, more educated mothers, who also have high non-labor incomes from their husbands, are able to drop out of the labor force and increase their time with the child when the child starts elementary school. Using geographic and time variation in private school cost, I estimate the price elasticity of private school enrollment to be -0.25. Moreover, a one standard deviation decrease in private school costs leads to incumbent mothers decreasing their work hours by less than 1%. However, mothers who select private schooling after the price decrease switch from part-time to full-time work to afford the private school tuition.

Finally, I conduct policy simulations to assess the impact of policies that subsidize private schooling. Most of the studies evaluating vouchers have focussed on its impact on student achievement. In contrast, my model allows me to study how subsidizing private school affects women's career paths and asset accumulation. I study two subsidy schemes. First, I simulate the impact of a subsidy with an asset test to explore if credit constraints affect investments in children's schooling.[5] Subsidizing private schooling for women with low assets increases private school enrollment, and allows credit constrained women to afford private schooling for their child. However, the effect on labor supply differs for incumbents and new entrants.[6] The subsidy acts as a work disincentive for incumbents, who reduce their work hours and see wage losses of 30% over the life cycle, while new entrants increase their labor supply to afford subsidized private schooling, which results in wage gains of 2%. Next, I give targeted subsidies of 25% to different education groups.[7] Results show that after the subsidy, less educated women switch from unemployment or part-time work to full-time work to afford the subsidized private schooling. Children of these women

[5] See [38] for a review of the importance of credit constraints on human capital accumulation.

[6] I define incumbents as mothers who were already selecting private school and new entrants as mothers who choose private school after the subsidy

[7] A 25% subsidy amounts to a one standard deviation decrease in private school costs.

see large gains in ability, and as a result of human capital accumulation over the life cycle, these women see wage gains of up to 20%. The higher wage income also allows these women to accumulate higher assets over the life cycle. These results show that targeted re-distributional policies can reduce inequality in children's outcomes, and can help women at the margin in the labor market.

1.2 Background, Data, and Descriptive Evidence

In this section, I give a brief background of private schooling in the US and present a simple two-period model to discuss the theoretical implications of the availability of private schooling on female labor supply and savings. I then introduce the data set used in the analysis and show how child's schooling choice interacts with maternal labor supply and asset holdings.

1.2.1 Private Schooling in the US

Data from the National Center for Education Statistics shows that private school enrollment in the United States has been fairly constant over the last decade 10%, which translates to 5.4 million children. Private schools constitute 25% of all US schools (30,861 schools in 2011-2012 school year). Within grades, a higher percentage of students are enrolled in private schools offering Pre-K through grade 8 (12.8%) than in schools offering grades 9 through 12 (8.0%). Private schools are also a more popular choice in the Northeast, where 14% of all enrolled students went to private school, as compared to the West, where only 8.0% of all enrolled students went to private school in 2011-12. Most private school students (79%) attend religiously-affiliated schools. While private school enrollment has not changed dramatically in the past decade, private school costs have risen substantially. Figure B.1 shows how the national average inflation-adjusted tuition has been evolving over the years for different types of private schools. The average tuition across all grades was $6,820 in the 1999-2000 school year and $10,940 in the 2011-2012 school year, which is an increase of around 60% in a little more than a decade. The bar chart also shows that the average tuition charged for all types of school has been increasing over the years, with the steepest rise for non-sectarian private schools. Schools associated with a religious congregation charge, on average, less than non-sectarian private schools. In the 2011-2012 school year, the cost of Catholic schooling was $7,020, as compared with $21,910 for non-sectarian private schools. These figures show that private schools are charging a non-trivial amount and that these costs have been rising at a higher rate than inflation in the past decade.

1.2.2 Theoretical Framework

In Appendix A.1, I present a simple stylized model of the effect of private schooling on maternal labor supply, savings and child outcomes which illustrates the trade-off women face between working and spending time with the child, and how that is affected by the availability and cost of private schooling. Theoretically, the introduction of private schooling into an environment where private schooling is not available as an option for child's schooling can lead to two possible labor supply responses from mothers. Mothers who choose to send their children to private school have to fund the additional cost of schooling, which would result in an increase in their labor supply. However, we could observe a decrease in mother's labor supply after the introduction of private schools if mother's time with the child and private school are complements, and if the marginal disutility from lower consumption is less than the marginal utility from higher child ability when the child goes to private school.

The trade-off women face can be expressed as follows: mothers will choose to work full-time and send their children to private school over not working and sending their children to public school if the marginal utility from the change in consumption – which includes monetary investments in the child – is greater than the marginal utility from the change in child ability. Simply put, the mother is more likely to increase her labor supply and select private schooling for the child if private school quality is considerably better than that in public school, so that the better school quality is enough to compensate for low maternal time investments. The female's time allocation decision also depends on the productivity of her time with the child. If mother's time with the child is not very productive, so that the drop in child ability is not large when the mother increases her labor supply, then the likelihood of working and selecting private school for the child would be higher. This effect is likely to be different for different women – for example, if we assume that mother's time with the child may be less productive for less educated females, we would expect to see these women work more when they send their child to private school, since the opportunity cost of staying at home for them is the highest (loss of wage earnings without a comparable boost in child ability). On the other hand, more educated mothers, who may be more productive at home with their child, might be more likely to stay at home with the child as the drop in child ability due to the mother spending less time with the child will be higher.

As for the the causal effect of a decrease private school fee, theoretically, a decrease in private school fee would unambiguously increase private school enrollment. However, the effect on maternal labor supply is different for incumbent mothers (mothers who were already selecting private schooling) and new entrants (mothers who select private schooling after the fee decrease). For incumbents, a decrease in school fee should unambiguously result in a decrease in labor supply. However, the effect on labor supply of new entrants is again theoretically ambiguous. These mothers will increase their labor supply if the marginal utility from higher child ability (due to the child attending good quality private school) is enough to compensate for the marginal disutility from lower net consumption. The direction of labor supply for new entrants will therefore depend on the magnitude of the fee decrease, as well as the complementarity between their time with the child and private schooling.

1.2.3 Private School and Maternal Labor Supply

I conduct a life cycle analysis with panel data to understand how mother's work decisions respond to child's school choice. The descriptive analysis reveals three key facts. First, we learn that women who send their children to private school are more educated and wealthier than women who send their children to public school. Second, I find that prior to childbirth, women who eventually select private school for their children work more, both at the extensive and the intensive margin, compared to public school mothers. However, a new and unexpected empirical fact is that this gap reverses after childbirth. Third, there is considerable heterogeneity across education and income groups in how private schooling interacts with labor supply. Low income and less educated mothers who send their children to private school work more throughout the life cycle, but for all other income and education groups, private school mothers work more in the years prior to their child's birth, but work substantially less than public school mothers after the child is born and starts school.

For my descriptive analysis, I use data from two main sources: NLSY79 and NLSY79 Child and Young Adult, and supplement it with time use data from the Panel Study of Income Dynamics (PSID) and private school fee data from `privateschoolreview.com`.

Details on the variables constructed from the various data sources are presented in Appendix A.2. I restrict my sample to ever married women in NLSY79.[8] I match the mothers in NLSY79 Child and Young Adult survey with the female respondents in NLSY79, so that my sample consists of all women in NLSY79 who have a child. I drop observations for which child's year of birth and schooling choice are not available, and only follow women after 18 years of age. The unit of analysis is a mother-child pair followed over time, and my sample consists of an unbalanced panel of 3,610 unique child-mother observations, 2,208 unique mother observations, and 76,143 total child-mother-year observations.[9] I am also able to extract demographic and labor market information about the females' spouses. Since NLSY79 does not have information on what type of private school the child goes to, the private school variable includes Catholic schools, schools with other religious affiliations, as well as non-sectarian private schools.[10] Out of the 3,610 children in the sample, 770 (21.3%) go to private school.

Summary statistics presented in Table B.1 show how private school mothers are observationally different from public school mothers. A higher proportion of mothers who send their children to private school are white and reside in urban areas. Private school mothers are also composed of more Roman catholics than public school moth-

[8] I drop cohabiting mothers from the sample. There are 545 single or cohabiting mothers in the sample, which constitutes 12.4% of total mothers.

[9] I treat children born to the same mother independent of their siblings.

[10] For my analysis, I construct a dummy variable $P \in \{0, 1\}$, which takes the value 1 if the female's child goes to private school and 0 otherwise. See Appendix A.2 for a detailed description of how this variable is constructed.

ers. As expected, mothers of private school going children are more educated, earn more wage and salary income and have more annual non-labor income at their disposal, with average non-labor income for private school mothers being approximately 1.7 times that of public school mothers.[11] These women also hold higher assets, as net worth of families with children going to private schools is approximately 2 times that of public school families. In Figure A.2, I plot the real net worth, defined as assets net of debt of the household, separately for mothers who send their children to private and public school. Consistent with the summary statistics, I find that throughout the child's life cycle, private school mothers have higher net worth than public school mothers. This reflects the difference in the savings and asset accumulation behavior of the two groups of women. There is also some evidence of positive assortative mating among private school parents, since spouse's annual earnings are higher, on average, for private school mothers.[12] The key variables of interest is mothers' employment rates and work hours. On average, private school mothers work more hours annually than public school mothers, an effect not being driven solely by a few women working more, since the annual employment rate of the former is 2% higher as well. Breaking up employment into full time and part time work reveals that 45% of private school mothers work full time, while in comparison, 43% of public school mothers work full time. Lastly, the standardized PPVT, PIAT-M and PIAT-R scores, as well as the

[11] Non-labor income is constructed by subtracting female's annual real wage income from annual real net family income.

[12] See [39] for a description of trends in private elementary school enrollment by family income from 1968-2013.

composite Test Score is higher for children who go to private schools.[13]

I study the direction of correlation between private school choice and labor supply of women in exploratory regressions presented in Table A.2. First, in Table A.2, Column (1) I report the predictors of private schooling. The probability of choosing private school for the child increases with mother's age, education level and non-labor income, but goes down with child age. Hispanic and white women are also more likely to choose private school for their children, as compared to African American women, with a higher proportion of white women choosing private schooling than hispanic women. Consistent with previous research [40], I also find that women who report some religion have a higher probability of choosing private school. Columns (2) and (5) show how annual hours and the probability of being employed are affected by key demographic variables. Annual hours worked and employment increase at a decreasing rate with age, and increase with female's education level. Married women and women with higher non-labor income work less hours annually, and both the extensive and intensive margin labor supply response also decreases with number of children in the household. All women who report a religion, other than Jewish women, work more hours annually. In Columns (3) and (6), I add the private school dummy as a regressor in the labor supply regressions and find that private schooling negatively impacts mothers' labor supply, both at the extensive and the intensive margin, even after controlling for demographic variables. Note that this is opposite

[13]The composite test score for each child is calculated by averaging the test scores available for each child. This ensures that I don't lose observations due to missing values of either test for any child.

in sign to the raw differences in annual hours worked and employment rates of private and public school mothers.

The regression results seem to suggest that women who choose private schooling for their children work less than public school mothers. However, labor supply patterns of females may differ over the life cycle because the value of female's time at home varies around childbirth, and as child starts school. Before the child is born, the opportunity cost of working is just foregone leisure. After childbirth, we would expect the mother's labor supply to drop due to two possible reasons: (1) there is an additional opportunity cost of working due to daycare costs, and (2) mother's time input directly impacts child ability, due to which mothers may decrease labor supply and spend time with the child. Once the child starts school, mother's time input is not as important to the child's development process, and school costs may drive up labor supply. Alternatively, mother's time and child's school quality may be complements, in which case mothers may decrease labor supply so that they can spend more time with their child to help with homework etc.

To see how labor supply patterns of private and public school mothers evolve, I estimate life cycle profiles of women who send their children to the two different types of schools over the age of the child.[14] In particular, I compare employment rates and average annual work hours of mothers over three phases of the life cycle: (i) till up to 6 years before childbirth, (ii) after childbirth but before child starts school and (iii)

[14] I run a kernel-weighted local polynomial regression of the dependent variable on child's age, and then present a non-parametric graph of the smoothed values.

after child starts school till age 12. Figures A.3 (a) and (b) plot employment rate and annual hours worked.[15] A higher percentage of mothers who send their children to private schools are employed 6 years before childbirth, with the employment gap between private and public school mothers around 7 percent. However, employment rate declines sharply around two years before childbirth, reaching the lowest point one and a half years after birth.[16] The gap between the employment rates for public and private school mothers then reverses when the child is approximately one and half years old. While employment rate for both groups of women is increasing, the increase is much steeper for public school mothers. Similarly, at the intensive margin, private school mothers work 400 hours more than public school mothers 6 years before birth, with the gap reversing when the child is approximately a year and a half.

These patterns suggest that there are dynamic interactions between private schooling and maternal labor supply. However, it is possible that observed differences in labor supply of private and public school mothers can be explained by selection on observables, notably, differences in education and non-labor income. Figures A.4 and A.5 present a comparison of hours worked by the two groups of women belonging to four education and non-labor income groups.[17] I find that high school dropouts who

[15] To formalize all results presented in the graphs, I also conduct a regression analysis that is presented in Appendix A.3.

[16] The drop in employment rates before childbirth may be explained by timing of marriage; when females get married, they quit work or reduce hours of work. The sample includes mothers with multiple births, so labor supply patterns will be affected by the number of children and spacing between births.

[17] I divide non-labor income into four quartiles. In my sample, non-labor income is distributed as follows: Quantile 1: $\leq$ \$6,207, Quantile 2: Between \$6,208 and \$21,384, Quantile 3: Between 21,385 and \$36,731, and Quantile 4: Between \$36,732 and \$1,167,736.

eventually send their children to private school work more than public school mothers with the same level of education before and after child birth. Similarly, among women whose non-labor income belongs to the bottom quartile of the distribution, private school mothers work more than public school mothers throughout the life cycle. For all other education and non-labor income groups, private school mothers are working more six years before the child is born, but work substantially less than public school mothers after the child is born and starts going to school. In particular, college graduates who send their children to private school drop their labor supply the most after child birth, particularly after the child starts school. This is informative about the trade-offs women with different levels of education face. For more educated and high income women, the value of female's time at home is higher, and is apparently higher for private school mothers after childbirth. This, coupled with the fact that these women have higher household income means that they can decrease their labor supply after childbirth and still afford expensive schooling for their children. For less educated and low income mothers who choose private schooling for their child, the marginal returns from working and affording private schooling for the child must be higher than the marginal returns from spending time at home.

Note that the observed choices different women make in the data could be due to differences in the budget constraint variables (wages, non-labor income, and school fee), differences in initial child ability, the child ability production function or a difference in preferences. To disentangle these channels and empirically investigate the effect of private schooling on women's career trajectories, I build a dynamic structural model in the next section which takes as ingredients the key lessons we learn from the descriptive analysis. In particular, the model allows for dynamics through asset and human capital accumulation, characterizes selection on observable and unobservable characteristics of the mother, and incorporates child's schooling decision in a standard life cycle model of female labor supply.

1.3 Dynamic Structural Model

I now present a dynamic structural model of female labor supply, savings and private school choice to empirically investigate the effect of the availability of private schooling on child ability and female life cycle outcomes. The model follows the spirit of standard structural models of female labor supply as in [41, 42, 43, 44, 13, 45]. As in these papers, I take women's fertility decisions to be exogenous. The novel ingredient in my framework is the introduction of child's schooling choice in the woman's problem. This allows me to capture the trade-off women face between working more to afford monetary investments in their children, or spending more time with the child. Additionally, it explicitly implements risk aversion and savings, thus taking into account the trade-off between building up assets before childbirth and take time off from work after childbirth. The key benefit of estimating the parameters of the structural model are that the model can be used to conduct counterfactual experiments that can be used to inform policy about private school subsidies and its effect on female labor supply and savings.

1.3.1 The Set-Up

The unit of analysis in the model is a single mother and child pair. However, to allow for the fact that women have more than one child, I allow for an exogenous process for fertility and let the number of children affect woman's utility and budget constraint. The model begins six years before the birth of a child and ends when the child finishes high school i.e. eighteen periods after childbirth. Time is discrete, with each period representing one year, so that I follow women for twenty-five periods. Entry into and exit out of marriage, and fertility are exogenous, as is husband's labor supply. In each period before childbirth, females choose consumption (and savings) and labor supply. If the woman works, she has to send her child to a daycare. In the sixth period, the females have a child, who is born with initial ability k_0, and child ability enters the female's utility function. In the initial five years of the child's life the child ability production function only takes in mother's time and goods investment as inputs. Five years after childbirth (in the twelfth period) mothers decide between private and public schooling for their child. Following that, the child ability production function takes as inputs mother's time, goods investment and schooling. Note that before childbirth females only have to allocate time between work and leisure, but after the birth of a child mother's time is allocated between work, leisure and time with the child. As in the descriptive analysis, I label the time periods before childbirth as phase 1, periods 6 till 11 as phase 2, and the time after child starts school as phase 3.

1.3.2 Choice Set

From periods 1 till 6, females make decisions about how much to consume ($c \geq 0$) and how to allocate time between work (h_{it}) and leisure (l_{it}). After childbirth, mothers allocate time between work, leisure and time with the child (τ_{it}). If the woman works when a child is present, she sends her child to daycare, which costs $\$cc_h$ per hour. In the twelfth period, five years after childbirth, in addition to the consumption and time allocation decisions, mothers make a decision about child's schooling, s_{it}, and chooses between private ($s_{it} = 1$) or public school ($s_{it} = 0$). Private and public schooling differ not just in terms of their price, but also in terms of their quality, which directly affects child ability. In each subsequent period, females continue to make consumption, time allocation and schooling choices.

In particular, the work alternatives for the female $d^h_{it} \in \mathcal{C}^h$ are defined as:

$$d^h_{it} = \begin{cases} 0 & \text{if } h_{it} = 0 \text{ hours} \\ 1 & \text{if } h_{it} = 1040 \text{ hours} \\ 2 & \text{if } h_{it} = 2080 \text{ hours} \end{cases}$$

where d^h_{it} is an indicator variable for hours worked. Before childbirth, the female's time allocation choices must satisfy the following constraint:

$$h_{it} + l_{it} = \bar{H} \equiv 2080 \tag{1.1}$$

After childbirth, the female's time constraint is given by:

$$h_{it} + l_{it} + \tau_{it} = \bar{H} \equiv 2080 \tag{1.2}$$

The mother now chooses her time at work, and the time spent with the child, for a total of 6 feasible time allocation choices:

$$d^h_{it} = \begin{cases} 0 & \text{if } h_{it} = 0 \text{ hours}, \tau_{it} = 0 \text{ hours} \\ 1 & \text{if } h_{it} = 1040 \text{ hours}, \tau_{it} = 0 \text{ hours} \\ 2 & \text{if } h_{it} = 2080 \text{ hours}, \tau_{it} = 0 \text{ hours} \\ 3 & \text{if } h_{it} = 0 \text{ hours}, \tau_{it} = 1040 \text{ hours} \\ 4 & \text{if } h_{it} = 1040 \text{ hours}, \tau_{it} = 1040 \text{ hours} \\ 5 & \text{if } h_{it} = 0 \text{ hours}, \tau_{it} = 2080 \text{ hours} \end{cases}$$

In order to make the choice set entirely discrete, I discretize the net savings choice $d^a_{it} \in \mathcal{C}^a$ so that the woman chooses one of 10 discrete alternatives $\Delta a_{it+1} = A_{it+1} -$

$(1+r)A_{it} = \{\underline{\Delta a}, \ldots, \overline{\Delta a}\}$ [46].[18] Finally, $d^s_{it} \in \mathcal{C}^s$ is an indicator variable for the child's schooling choice which is 1 when child goes to private school, and 0 otherwise. The choice set $\mathcal{C}$ in each period is constructed by the Cartesian product of the set of discrete alternatives ($\mathcal{C}^h \times \mathcal{C}^a$ in phases 1 and 2, and $\mathcal{C}^h \times \mathcal{C}^a \times \mathcal{C}^s$ in phase 3). This means that the woman has 30 choices in phase 1, 60 choices in phase 2, and 120 choices in phase 3.

1.3.3 State Space

At the start of each period, agents take as given the variables that form their state space. For ease of writing the value functions, I define three state vectors, one for each phase of the woman's life cycle. For the first phase, the state vector is defined as:

$$\Omega^1_{it} = \left\{A_{it}, H_{it}, n^k_{it}, educ_i, race_i, \mu_i, \Psi, \xi_{it}, \xi^h_{it}\right\} \tag{1.3}$$

where A_{it} is the asset stock available at the start of the period, H_{it} is the stock of human capital up till period t, and n^k_{it} is the number of children at period t. The state space vector also includes time-invariant unobserved type, a vector of iid shocks to preferences affecting female's decisions, collected in Ψ, and shocks to the female's wage and husband's earnings process, ξ_{it} and ξ^h_{it}.

In the second phase of the life cycle, child ability enters the utility function so

[18] I set $\underline{\Delta a} = -\$5,000$ and $\overline{\Delta a} = \$20,000$ and evenly distribute the rest of the net savings alternatives between these extremes. Through her choice of net savings, the woman also decides her consumption level in period t.

that the state vector during this phase is defined as:

$$\Omega_{it}^2 = \Big\{A_{it}, H_{it}, k_{it}, n_{it}^k, educ_i, race_i, \mu_i, \Psi, \xi_{it}, \xi_{it}^h, \eta_{it}\Big\} \tag{1.4}$$

where k_{it} is child cognitive ability in period t and η_{it} is an iid shock to child ability.

In the third phase, schooling choice also enters the optimization problem, and private school fee p_{it} is added to the state space:

$$\Omega_{it}^3 = \Big\{A_{it}, H_{it}, k_{it}, n_{it}^k, p_{it}, educ_i, race_i, \mu_i, \Psi, \xi_{it}, \xi_{it}^h, \eta_{it}\Big\} \tag{1.5}$$

See Table A.3 for a list of all state space variables in the three phases.

1.3.4 Preferences

I assume that utility is intertemporally separable, and that per period utility defines the woman's preferences over l_{it}, c_{it}, k_{it} and s_{it}, given her information set at time period t, I_{it}. The woman's instantaneous utility is given by:

$$\begin{aligned} U_{it}(c_{it}, l_{it}, k_{it}, s_{it}; I_{it} \in \{\Omega_{it}^{phase}\}) = f^c(X_{it}, \mu_i)\frac{\left(\frac{c_{it}}{e_{it}}\right)^{\alpha_1}}{\alpha_1} + f^h(X_{it}, \mu_i) l_{it} \\ + f^k(X_{it}, \mu_i)\mathbf{1}\{a_t > 0\}\Big(\frac{k_t^\lambda - 1}{\lambda}\Big) \\ + f^s(X_{it}, \mu_i)\mathbf{1}\{a_t \geq 5\}\mathbf{1}\{s_{it} = 1\} \end{aligned} \tag{1.6}$$

Instantaneous utility is separable between consumption and leisure. The equivalence scale for consumption is given by e_{it}, which depends on the age and number of children in the household. I use the McClements scale to determine e [11].[19] The utility from consumption has an augmented CRRA form, with the constant relative risk-aversion parameter given by $1-\alpha_1$, while f^c reflects how the marginal utility of consumption is affected by differences in observable and unobservable characteristics of the females [46, 11, 15, 45]. Specifically, the function is defined as

$$\begin{aligned} f^c(X_{it}, \mu_i) = \exp\big(&\gamma_0^c + \gamma_1^c \mathbf{1}\{a_t \leq 5\} + \gamma_2^c \mathbf{1}\{a_t \geq 6\} + \gamma_{3e}^c \sum_{e=2}^{3} \mathbf{1}\{\text{educ} = e\} \\ &+ \gamma_4^c n_{it}^k + \gamma_{5l}^c \sum_{l=1}^{L} \mathbf{1}\{\mu_i = l\}\big), \end{aligned} \tag{1.7}$$

where a_t is child's age at time period t, e represents the education group the female belongs to, with $e=1$ if the woman is a high school dropout, $e=2$ if she finished high school, and $e=3$ for some college or above, and n_{it}^k is the number of children individual i has at time t. Permanent unobserved heterogeneity enters the model through woman's latent type $\mu \in \{1, \dots, L\}$, and captures individual's preference for leisure and saving.[20] The second component of instantaneous utility represents the utility from leisure. The function f^h represents how the marginal utility of leisure/marginal

[19] According to the McClements scale, a childless couple is equivalent to 1.67 adults. A couple with one child is equivalent to 1.9 adults if the child is under the age of 3, to 2 adults if the child is between 3 and 7, 2.07 adults if the child is between 8 and 12, and 2.2 adults if the child is between 13 and 18.

[20] The latent type affecting the marginal utility from consumption, leisure and private schooling essentially captures the correlation between unobserved preferences and labor market skill.

disutility of working changes with female's observed and unobserved characteristics. In particular, I specify

$$f^h(X_{it}, \mu_i, \epsilon_{it}^h) = \gamma_0^h + \gamma_1^h \mathbf{1}\{a_t \leq 5\} + \gamma_2^h \mathbf{1}\{a_t \geq 6\} + \gamma_{3e}^h \sum_{e=2}^{3} \mathbf{1}\{\text{educ} = e\} \qquad (1.8)$$
$$+ \gamma_4^h n_{it}^k + \gamma_{5h}^l \sum_{l=1}^{L} \mathbf{1}\{\mu_i = l\} + \epsilon_{it}^h,$$

where $\epsilon_{it}^h \sim \mathcal{N}(0, \sigma_{\epsilon^l}^2)$ is an iid preference shock for the relevant time allocation decision. The third component of instantaneous utility is child's cognitive ability, k_t. Note that child's cognitive ability enters the utility function only after the child is born i.e. when child's age is non-negative. The mother gets utility from child ability according to a CRRA function with parameter λ, while f_t^k captures differences in the marginal utility from child ability due to differences in mother's observed and unobserved characteristics [23]. In particular,

$$f^k(X_{it}, \mu_i) = \gamma_0^k + \gamma_1^k \mathbf{1}\{a_t \leq 5\} + \gamma_2^k \mathbf{1}\{a_t \geq 6\} + \gamma_{3e}^k \sum_{e=2}^{3} \mathbf{1}\{\text{educ} = e\} \qquad (1.9)$$
$$+ \gamma_4^k n_{it}^k + \gamma_5^k m_{it} + \gamma_{6l}^k \sum_{l=1}^{L} \mathbf{1}\{\mu_i = l\},$$

where m_{it} is the female's marital status with $m_{it} = 1$ if she is married and 0 otherwise. Finally, I introduce heterogeneity in the utility from private schooling through

$f^s(X_{it}, \mu_i, \epsilon^s_{it})$, which is specified as:

$$f^s(X_{it}, \mu_i, \epsilon^s_{it}) = \gamma^s_0 + \gamma^s_{1e} \sum_{e=2}^{3} \mathbf{1}\{\text{educ} = e\} + \gamma^s_2 n^k_{it} + \gamma^s_{3l} \sum_{l=1}^{L} \mathbf{1}\{\mu_i = l\} + \epsilon^s_{it}, \qquad (1.10)$$

where $\epsilon^s_{it} \sim \mathcal{N}(0, \sigma^2_{\epsilon^s})$ is an iid preference shock for private schooling.

1.3.5 Child's Cognitive Ability

I assume that a child is born with initial ability endowment of k_0, which is a function of mother's observed and unobserved characteristics. Specifically,

$$\ln(k_0) = \gamma^{k_0}_0 + \gamma^{k_0}_{1e} \sum_{e=2}^{3} \mathbf{1}\{\text{educ} = e\} + \gamma^{k_0}_2 \text{race} + \gamma^{k_3 l}_0 \sum_{l=1}^{L} \mathbf{1}\{\mu_i = l\}, \qquad (1.11)$$

where child ability endowment is affected by mother's unobserved type, μ_i, as well as observed characteristics such as education and race.

Given the initial ability endowment of the child, I can now define the cognitive ability production function, which is a function of child ability stock till last period, mother's time with the child, goods inputs and schooling. I assume a modified translog for the child ability production function [47], specified as:

$$\begin{aligned}\ln k_{it+1} = {} & \beta_0 + \beta_1 \ln k_{it} + \beta_2(X_{it}, \mu_i) \ln \tau_{it} + \beta_3 \ln G_{it} \\ & + \mathbf{1}\{a_t^k \geq 6\}\beta_4 s_{it} + \beta_5(\ln k_{it} \times \ln \tau_{it}) + \beta_6(\ln k_{it} \times \ln G_{it}) \\ & + \beta_7(\ln \tau_{it} \times \ln G_{it}) + \mathbf{1}\{a_t^k \geq 6\}\Big(\beta_8(\ln k_{it} \times s_{it}) + \beta_9(\ln \tau_{it} \times s_{it}) \\ & + \beta_{10}(\ln G_{it} \times s_{it})\Big) + \eta_{it},\end{aligned} \tag{1.12}$$

where

$$\begin{aligned}\beta_2(X_{it}, \mu_i) = {} & \pi_0^\tau + \pi_1^\tau \mathbf{1}\{a_t \leq 5\} + \pi_2^\tau \mathbf{1}\{a_t \geq 6\} + \pi_{3e}^\tau \sum_{e=1}^{3} \mathbf{1}\{\text{educ} = e\} \\ & + \pi_4^\tau m_{it} + \pi_5^\tau n_{it}^k + \pi_{6l}^\tau \sum_{l=1}^{L} \mathbf{1}\{\mu_i = l\}.\end{aligned} \tag{1.13}$$

In equation (1.12), k_t is the child ability stock at time t, τ_{it} is mother's time investment in period t and G_{it} is the goods investment by parents. Since goods investment is not observed in the data or modeled as a choice, I assume that G_{it} is a fixed proportion α_G of family income (woman's wage income plus husband's income if married) which is estimated within the model. After five years of age, the child starts school and a dummy for private schooling is added to the production function as an input. The interaction terms between s_{it}, G_{it} and τ_{it} capture static complementarity i.e. returns to current investments should depend on other investments. By modeling the interaction between maternal investments and private schooling, I am also able to show how the effect of private schooling on student achievement found in the literature work through mechanisms involving women's labor supply. The technology of child ability production also exhibits dynamic complementarity, which suggests that returns to current investment depend on $\ln k_{it-1}$. β_0 is a total factor productivity parameter and $\eta_{it} \sim \mathcal{N}(0, \sigma_\eta^2)$ is a time-varying idiosyncratic shock to ability that is realized after the woman has made all her decisions. I allow the coefficient on $\ln \tau_{it}$ to be a function of female's observed and unobserved characteristics, which means that the productivity of mother's time with the child varies across females. The function $\beta_2(X_{it}, \mu_i)$ is specified in equation (1.13) and shows that mother's productivity with the child depends on her latent type, her education level, child's age, number of children and marital status.

1.3.6 Number of Children

Fertility is treated as an exogenous process in the model, with one child entering deterministically in period 6. The other children in the household can enter the household at any time, and the transition in the number of children is modeled to match the dynamics in the data. To limit the size of the state space I cap the total number of children a woman can have to 2 (including the child that enters deterministically). The transition in the number of other children is specified as follows:

$$P(n_{it+1}^k = 1 | n_{it}^k = 0) = \frac{\exp(\delta_0^n + \delta_1^n age_{it} + \delta_2^n \text{race} + \delta_3^n \sum_{e=2}^{3} \mathbf{1}\{\text{educ} = e\} + \delta_4^n m_{it})}{1 + \exp(\delta_0^n + \delta_1^n age_{it} + \delta_2^n \text{race} + \delta_3^n \sum_{e=2}^{3} \mathbf{1}\{\text{educ} = e\} + \delta_4^n m_{it})}, \quad (1.14)$$

where the probability of having a child in the next period is a function of the woman's age, marital status, education and race.

1.3.7 Marriage and Divorce

The probability of marriage in each period is a function of the woman's demographics $\tilde{X}_{it}$ which includes the woman's age, race, education and child's age and is defined as:

$$P(m_{it}=1|m_{it-1}=0)=\frac{\exp(\delta_0^m+\delta_1^m(age_{it})+\delta_2^m\text{race}+\delta_3^m\sum_{e=2}^{3}\mathbf{1}\{\text{educ}=e\}+\delta_4^m\mathbf{1}\{a_t>6\})}{1+\exp(\delta_0^m+\delta_1^m(age_{it})+\delta_2^m\text{race}+\delta_3^m\sum_{e=2}^{3}\mathbf{1}\{\text{educ}=e\}+\delta_4^m\mathbf{1}\{a_t>6\})}, \tag{1.15}$$

Conditional on being married, the probability of divorce is given by:

$$P(m_{it}=0|m_{it-1}=1)=\frac{\exp(\delta_0^d+\delta_1^d(age_{it})+\delta_2^d\text{race}+\delta_3^d\sum_{e=2}^{3}\mathbf{1}\{\text{educ}=e\}+\delta_4^d\mathbf{1}\{a_t>6\})}{1+\exp(\delta_0^d+\delta_1^d(age_{it})+\delta_2^d\text{race}+\delta_3^d\sum_{e=2}^{3}\mathbf{1}\{\text{educ}=e\}+\delta_4^d\mathbf{1}\{a_t>6\})}. \tag{1.16}$$

1.3.8 Budget Constraint

The female maximizes her utility subject to a budget constraint that keeps evolving over the three phases of the woman's life cycle. The budget constraint can be described in terms of the following asset evolution equation:

$$\begin{aligned} A_{it+1} &= (1+r)A_{it}+h_{it}w_{it}+m_{it}(\text{earn}_{it}^h\times 52)-c_{it}-CC^k n_{it}^k \qquad (1.17)\\ &\quad -\mathbf{1}\{a_t>0\}G_{it}-\mathbf{1}\{0\leq a_t<5\}\Big(cc_h*h_{it}\Big)-\mathbf{1}\{s_{it}=1\}p \end{aligned}$$

$$c_{it} \geq \underline{c} \tag{1.18}$$

$$A_{it+1} \geq \underline{b} \tag{1.19}$$

where A_t is the accumulated savings from last period, r is the risk-free interest rate, w_{it} is the wage rate of the woman, while $earn^h_{it}$ denotes husband's weekly earnings. Equation 1.18 imposes the borrowing constraint which requires assets to stay above a non-positive number, $\underline{b}$, every period. The woman incurs childcare costs after childbirth and before child starts school. cc_h is the hourly childcare rate, so that her total childcare cost depends on total hours worked in the year. CC^k is the annual cost associated with other children in the household and includes goods investment, schooling costs (if any), as well as psychic costs.[21] Finally, p is private school fee, which is incurred only if the child goes to private school. I also assume that there exists a consumption floor $\underline{c}$, such that any choice tuple $(d^h_{it}, d^a_{it}, d^s_{it})$ is feasible only if household consumption is above $\underline{c}$.

The woman's wage process can defined as an exponential function of the woman's ability, work status (part-time versus full-time), age, race, education and experience

[21] Since I do not have data on expenditure on children, or have data on schooling for every sibling, I am allowing for number of children to affect the budget constraint faced by the woman without explicitly modeling the school choice for each child. The current model explicitly models only one child and sidesteps the issue of mother's time allocation and schooling decisions for multiple children in the same household. The time the mother decides to spend with a child, and the type of school the child goes to, can be affected by the presence of other siblings in the household, which is captured by adding the number of children as utility and productivity shifters in the current model. A natural extension of the above model would be to model fertility and time allocation and schooling decisions across each child in a family explicitly.

stock. Specifically, the female wage process is given by:

$$\begin{aligned}\ln w_{it} = \gamma_0^w + \gamma_{1e}^w \sum_{e=1}^{3} \mathbf{1}\{educ = e\} + \gamma_2^w race_i + \gamma_3^w \ln(H_{it}+1)_{it} \\ + \gamma_4^w (\ln(H_{it}+1))_{it}^2 + \gamma_{5l}^w \sum_{l=1}^{L} \mathbf{1}\{\mu_i = l\} + \xi_{it}, \qquad \xi_{it} \sim \mathcal{N}(0, \sigma_\xi^2)\end{aligned} \tag{1.20}$$

$$H_{it} = H_{it-1} + h_{it} \tag{1.21}$$

where H_{it} is the accumulated stock of experience and ξ_{it} is an iid shock to log wages. γ_3^w and γ_4^w captures the returns to experience, γ_7^w reflects the impact of female's innate skill on her wage earnings and γ_4^w captures differences in wage due to racial discrimination. The experience accumulation process is defined in equation (1.21).

I model the husbands' weekly earnings, $earn_{it}^h$ as an exogenous process that captures both their labor supply and wages. I assume that husband's earnings depends on the wife's observed and unobserved characteristics, as in [15], [10] and [43]. This allows me to keep the state space small, yet also capture the essential ingredients of a model with marriage market, which would predict positive assortative mating and heterogeneity in female's marriage decisions. The husband's earnings is given by:

$$\begin{aligned}earn_{it}^h = \gamma_0^{y^h} + \gamma_{1e}^{y^h} \sum_{e=2}^{3} \mathbf{1}\{\text{educ} = e\} + \gamma_2^{y^h} race_i + \gamma_3^{y^h} t + \gamma_3^{y^h} t^2 \\ + \gamma_{5l}^{y^h} \sum_{l=1}^{L} \mathbf{1}\{\mu_i = l\} + \xi_{it}^h, \qquad \xi_{it}^h \sim \mathcal{N}(0, \sigma_{\xi^h}^2)\end{aligned} \tag{1.22}$$

where γ_1^{wh} and γ_2^{wh} capture assortative mating on woman's education and race, γ_3^{wh} captures assortative mating on unobserved type, t is a time trend, and ξ_{it}^h is husband's earnings shock.

1.3.9 The Woman's Problem

I can now write down the woman's maximization problem given her choice set and preferences. The woman maximizes her expected lifetime utility, starting 6 years before birth at time period t_0, and ending 24 periods later when the child completes high school. Since the state space changes after childbirth, the woman's maximization problem can be written separately for the three phases of the female's life cycle: before childbirth, after childbirth and before child starts school, and after child starts primary schooling. The value function for individual i in period t, before the birth of the child, can be defined as:

$$V_t(\Omega_{it}^1) = max_{\{d_{it}^a, d_{it}^h\}} U_{it} + \beta E_t \Big[V_{t+1}(\Omega_{t+1}^1) \Big], \tag{1.23}$$

where β is the discount factor and E_t is the expectation operator conditional on information in period t. The expectation is taken over the vector of preference shocks, Ψ_{it+1}, future wage and earnings shocks ξ_{it+1} and ξ_{it+1}^f, and shocks to child ability η_{it}.[22] In the sixth period, the child is born, and the woman's state space changes to $\tilde{\Omega}_{it}$ as

[22] All preference shocks follow Normal distribution with mean 0.

child ability enters her utility function. The value function for individual i in period t following the birth of the child till the child starts school 5 periods later, can be written as:

$$V_t(\Omega_{it}^2) = max_{\{d_{it}^a, d_{it}^h\}} U_{it} + \beta E_t \Big[V_{t+1}(\Omega_{t+1}^2) \Big], \tag{1.24}$$

Finally, in period 11, the female has to make a choice about child's schooling, so that from period 11 till the terminal period, she has to make three choices: c_{it}, h_{it} and s_{it}. Formally, the value function after period 11 can be written as:

$$V_t(\Omega_{it}^3) = max_{\{d_{it}^a, d_{it}^h, d_{it}^s\}} U_{it} + \beta E_t \Big[V_{t+1}(\Omega_{t+1}^3) \Big], \tag{1.25}$$

The model ends when the child leaves high school at age 18, $T = 25$. The terminal value function consists of contemporaneous utility, and expected utility from child's lifetime earnings:

$$V_T(\Omega_{iT}^3) = U_{iT}(c_{iT}, h_{iT}, k_{iT}) + \gamma_1^T A_{iT} + \gamma_2^T k_{iT}. \tag{1.26}$$

where γ_1^T captures the value from accumulated assets in period T and γ_2^T captures the utility from child cognition in period T.

1.3.10 Unobserved Heterogeneity

Permanent unobserved heterogeneity among females, denoted by μ, affects the utility from leisure, consumption and private schooling as well as returns to work and time spent with the child. μ captures the persistent heterogeneity that drives otherwise identical women to persistently behave differently across their choices and outcomes over time.[23] The heterogeneity is modeled as discrete mass points [48], which are allowed to be functions of female's education level, given by:[24]

$$\pi_\mu = \frac{\exp(\alpha^\mu_{0j} + \alpha^\mu_{1je} \sum_{e=2}^{3} \mathbf{1}\{\text{educ} = e\})}{1 + \sum_{l=2}^{L} \exp(\alpha^\mu_{0l} + \alpha^\mu_{1le} \sum_{e=2}^{3} \mathbf{1}\{\text{educ} = e\})}, \qquad \forall \mu \in \{2, \dots, L\} \tag{1.27}$$

$$\pi_1 = 1 - \sum_{\mu=2}^{L} \pi_\mu \tag{1.28}$$

1.4 Estimation and Results

In this section, I first outline the estimation procedure for the dynamic optimization problem, and then present the identification arguments. Next, I discuss the parameter estimates and show how child's schooling choice affects life cycle female labor supply, asset distribution and the evolution of child ability.

[23] The latent types capture both unobserved differences in productivity and unobserved differences in preferences.

[24] I assume that educational attainment of a woman is exogenous conditional on her latent type.

1.4.1 Estimation Method and Moments

I use a two-step procedure to estimate the parameters of the structural model. In the first step, I estimate the probability of entry and exit into marriage and the transition in the number of children using data from NLSY79. In addition, I set the discount factor to 0.98, the risk-free interest rate to 0.02, and the hourly daycare cost to the national average obtained from the Bureau of Labor Statistics, \$9.77. In the second step, I estimate the remaining 107 parameters of the model using the Method of Simulated Moments (MSM). In this approach, the model is solved by backwards induction (value function iterations) based on an initial set of parameters, and then simulated for individuals over their life cycle.

In particular, I first estimate the exogenous processes of marriage and fertility from the data and set the discount factor, interest rate and hourly daycare cost. Given these parameters and an initial guess of the remaining model parameters, I solve the life cycle optimization problem of the woman by backward recursion. Backward recursion entails solving the model as a function of the entire state space for each period. More specifically, the solution requires finding values of $E_t\Big[V_{t+1}(\Omega_{t+1})\Big]$ at each point on the state space, which is computationally burdensome. To reduce the computational burden, I discretize the continuous state variables A_{it}, H_{it}, k_{it} and p_{it} and use linear interpolation to extrapolate for any values that fall outside the state space grid. Calculation of $E_t\Big[V_{t+1}(\Omega_{t+1})\Big]$ also requires the calculation of multivariate integrals which is done by Monte Carlo integration.[25] While discretization makes the state space finite, it still remains large, making the estimation computationally infeasible. In order to further reduce the computational burden associated with the iterative process, I implement a computationally feasible Bayesian approach for solving the model developed by [50] and [51] that relies on Markov Chain Monte Carlo (MCMC) methods.[26] The details of the algorithm are presented in Appendix C.3.

After solving the model, I simulate choices for 15,000 women (5 paths for each mother-child pair in the sample), reproducing the structure of the data, and calculate moments using the simulated data.[27] I then calculate the weighted average distance between the simulated moments and moments constructed from the sample data. This iterative process is repeated till the distance is minimized. Formally, let Θ denote the parameter vector, $M_S(\Theta)$ denote the vector of moments calculated using the simulated data and M_N denote the vector of moments from the observed data. Then, the estimated parameter vector $\hat{\Theta}$ solves the following objective function

$$\hat{\Theta} = \arg\min_{\Theta}(M_N - M_S(\Theta))' W_N (M_N - M_S(\Theta)), \tag{1.29}$$

where W_N is a positive-definite, symmetric weighting matrix.

[25] See [49] for details on various methods of obtaining approximate solutions to DDCP in labor economics.

[26] The traditional Bayesian approach is typically intractable for dynamic discrete choice problems [52].

[27] The estimation sample is a subset of the sample used for the descriptive and reduced form analysis. To construct the estimation sample for the structural estimation, I only keep mother-child pairs who I can follow for the entire 25 periods i.e. from six years before childbirth till the child is 18 years of age. This condition leaves me with a total of 3000 mother-child pairs.

As shown in [53], method of simulated moments yields consistent estimates, though its finite distance properties depend on the choice of moments, the number of simulations, and the weighting matrix and that conditional dynamic moments are crucial to identify the parameters of dynamic models such as the one specified in this paper. Therefore, I follow [53] and weight the moments with a diagonal matrix that contains the inverse of the variances of the observed moments.[28] The moments used for estimation include the proportion of women employed in each time period, across child schooling groups and woman's education groups, work experience accumulated by private and public school mothers, and the proportion of women working full-time and part-time in each time period. The returns to private schooling parameters are identified by matching moments on the proportion of women sending their child to private school at each child age group by women's education, and the ratio of test scores of private and public school children. Mother's time with the child parameters are identified by matching the proportion of mothers spending full-time, part-time or no time with their children, for different education and child age groups. Dynamic moments include transition rates between labor market status by child's schooling and phase, the correlation between wage at the start of each phase and an OLS regression of log wage on past and future wages.

[28]The vector M_N consists of a total of 448 moments that are used to identify 107 parameters.

1.4.1.1 Initial Conditions and Measurement Error

The initial conditions of the model consist of values of woman's education, race, the number of children she has, her state of residence, the level of net assets she holds, and the experience accumulated at t_0, which is six years before the birth of the child. Values of woman's education, race, state of residence, experience accumulated and level of net assets are taken as given in the data. For women whose net assets are missing six years before childbirth, I draw a value for net assets from the distribution of real net assets conditional on the woman's education level.

Data on private school costs faced by women is only available at the state level. However, due to the availability of financial aid as well as variation within a state in the sticker price for private schooling, the state level averages are not a good measure of the actual cost of private schools that mothers face. Therefore, I assume that tuition data I have is measured with error, so that the true tuition faced by mothers is given by:

$$p_{it}^{true} = \alpha^p + \beta^p p_{it}^{observed} + \eta_{it}^p, \quad \eta_{it}^p \sim \mathcal{N}(0, \sigma_p^2) \tag{1.30}$$

where α^p is the location parameter, β^p is the scale parameter and η^p is an iid shock that follows a Normal distribution with mean 0 and variance σ_p^2. Any measurement error in wages and in child ability is assumed to be captured by the idiosyncratic shocks ξ_{it} and η_{it}.

1.4.2 Identification

This section discusses sources of identification in the model. The identification of the parameters of the model rely on a combination of functional form and distributional assumptions, exclusion restrictions delivered by the structure of the model and arguably exogenous cross-sectional variation in private school fee.

One source of identification relies on exclusion restrictions delivered by the structure of the model. The first set of exclusion restrictions require that there must be at least one variable that enters the selection equations (e.g. work, private school, consumption), but does not affect the outcome equations (e.g. wages, child ability). An example is the number of children a woman has, which shifts the marginal utility from leisure but does not enter the wage equation.[29] The second set of exclusion restriction necessitates that there must be one variable in the outcome equation that does not affect selection into certain states. In the model, experience, which enters the wage equation but does not affect the utility from leisure, serves as an example of the second set of exclusion restrictions. A similar argument can be made for the budget constraint parameters. Experience and race affect wage and husband's earnings, therefore affecting the budget constraint and the child ability production function, but does not affect the marginal utility from consumption, private schooling and child ability.

The coefficient of relative risk aversion, α_1, which determines the curvature of the

[29] While the number of children the woman has is endogenous, the arrival rate of children is exogenous.

utility function and the intertemporal elasticity of substitution, is identified through differences in the net saving-child age profiles of women who are otherwise identical. I also specify the marginal utility of consumption as an exponential function, that aids in identification. Similarly, the CRRA parameter for child ability λ is identified through differences in maternal time investment in their children for women who have similar observed and unobserved characteristics. To identify the effect of private schooling on maternal labor supply and savings, I use cross-sectional variation in private school fee to instrument for private school enrollment. Figure A.6 plots the cross-sectional variation in private school fee and shows that, as expected, private school enrollment decreases as private school fee increases.[30] The identification argument relies on the assumption that variation in private school fee should affect private school enrollment but should not be correlated with women's work decisions i.e. private school fee should affect female labor supply and savings only through its affect on private school enrollment. I also use the cross-sectional variation in private school fee to help identify λ and the unobserved preference for private schooling. Suppose two observably identical women are living in different geographic area with different private school tuition, with one woman living in a high cost area, and the other living in a low cost area. If the woman living in the high cost area is observed choosing private schooling yet the woman living in the low cost area does not choose private schooling for her child, the difference in choices must be driven by difference

[30]Reduced form results for the effect of private schooling on female labor supply and assets using private school fee as an instrument for private schooling are available upon request from the author.

in preferences for private schooling and child ability.

The distribution of latent types and type-specific parameters are identified through the panel structure of the data. In particular, differences in choices and outcomes of observationally identical women over time identifies latent types. In order to identify the proportion of individuals in each latent type, I follow [15] and first regress log wages on experience and education and compute wage residuals for each individual. This residual contains information on unobserved skill or ability. I then use the cross-sectional variance of these wage residuals as a moment. As types cannot be identified without a normalization, I impose a ranking on the latent types in estimation. I assume type 1 women have the lowest latent ability endowment while type 3 women have the highest.

1.4.3 Parameter Estimates

I present estimates for the preference parameters in Table A.4.[31] The CRRA parameter is estimated to be 0.354, which implies that the coefficient of relative risk aversion is $1 - \alpha_1 = 0.65$, and the coefficient of relative prudence is $2 - \alpha_1 = 1.65$ which is in line with other papers in the literature with borrowing constraints ([46]; [54]).[32] Estimates also show that higher number of children and having a child greater

[31] Estimates from the first step of the estimation procedure outlined in Section 3.4 are presented in Appendix A.4.2. Predicted probabilities based on these estimates are then used as an input for the second step of the estimation in which the life cycle optimization problem is solved by value function iterations.

[32] The literature on the estimation of consumption Euler equation has estimated $\alpha_1 = -2$ [55, 56], which implies a lower willingness to substitute intertemporally and higher degree of prudence than

than six years of age increases the marginal utility from consumption. Having more children also increases the marginal utility from leisure. Estimates for the leisure preference parameters also show that mothers with older children value leisure more than mothers with younger children. Lastly, the private school preference parameters show that women with college degree or more gain 3.5 times as much utility from choosing private schooling for their child as women with only a high school degree.

Table A.5, panel (a) shows the results for the wage equation. The parameters for the wage equation are consistent with those reported in the female labor supply literature. If females have some college, college or graduate degree, they earn approximately 46% higher wages than high school dropouts. Estimates for the polynomial in experience show that the returns to experience are increasing at a decreasing rate. Therefore, for a woman with 5 years of full-time experience, the returns to a 1% increase in experience stock is 0.061%, while the returns to a 1% increase in experience for a woman with 10 years of full-time experience is 0.062%. This implies that a woman who has worked full-time for 10 years will be offered a wage that is 6.2% higher than a woman who has worked part-time for 10 years. The estimates also show that black women earn 11% lower wages than women of other racial groups, which could be due to racial discrimination in the labor market or due to unobserved differences in black women's skill endowment not captured by the latent type. Panel

that estimated in this paper. [46] rationalize different estimates from the literature by noting that in models with income uncertainty and no borrowing constraints, a higher degree of prudence is required to explain why individuals with steep age-earnings profiles do not borrow when they are young.

(c) of Table A.5 shows that women cannot borrow more than \$41,520, and that they must maintain at least \$164 in consumption. The average cost of additional siblings in the household (including both monetary and psychic costs) is \$3,903 and households spend 3% of their income on their child, which is in addition to expenditure on child's school tuition.

1.4.3.1 Child Ability

The CRRA parameter for child ability is estimated to be 0.49, which is in line with an estimate of 0.46 presented in [23]. The parameter estimate implies that mothers get diminishing marginal utility from child ability and therefore have an incentive to make investments to compensate children born with low ability endowments. The preference parameters for child ability show that the marginal utility from child ability is higher when the child is less than six years of age (the first and formative phase of development), and that more educated mothers value higher child ability more than mothers who are high school dropouts. The presence of a husband also increases the marginal utility of children, while having more children decreases the utility from having a child.

Panel (f) of Table A.4 shows the estimates of the child ability production function. Estimates show that the net effect of attending private school on child achievement is positive and depends on lagged ability, mother's time with the child and the level of goods investments. In particular, mother's time and private schooling are complements, which suggests that mothers may have to spend time with their children to help them with the private school curriculum. Using the estimates of the child ability production function, I can calculate the effect of private schooling on twelfth grade scores, and compare the results to those reported in [29]. On average, mothers spend no active time with their child when the child is in twelfth grade. Therefore, using the sample averages of test scores and log family income from [29], the twelfth grade test score for a child with eleventh grade test score of 53.5 and whose parents have household income of $\$36,316$ would be 7.8% higher if he attends private school.[33] Increasing goods investment by 1% increases next period ability by 0.99% while increasing current period ability by 1% increases next period ability by 0.01%. The interaction terms between $\ln k_t$ and investments show evidence of dynamic complementarity for mother's time with the child and private schooling i.e. mother's time and private schooling are more productive for higher ability children. However, lagged cognition and goods investment are substitutes. Table A.4 panel (g) shows how the productivity of mother's time is affected by her demographic characteristics. Mother's time is 1.9 times more productive when the child is less than six years of age than when he is older. More educated mothers are also more productive at home, and the presence of a husband and having siblings also increases mother's productivity

[33]This estimate is higher than the effect of private schooling on students' math scores found in [29], who find that math scores increase by 1.14 points, which translates to a roughly 2.1% increase. I find larger effects of private schooling, which can be attributed to the fact that I am not just focussing on Catholic schools, as in [29], but looking at the overall impact of all types of private schooling. This suggests that the positive effect of non-sectarian and other religious private schools is higher than the effect of just Catholic schools.

with the child. These results imply that mothers would make greater investments of their own time in producing child quality prior to and concurrent with schooling, which is consistent with the results reported in [57].[34]

1.4.3.2 The Role of Unobserved Heterogeneity μ

Latent heterogeneity plays an important role in the model, even after controlling for a rich set of observable characteristics. I allow for 3 types and impose an ordinal ranking on the types, ascending from type 1. Estimates imply that more educated mothers are more likely to be of type 3 while low education negatively predicts the probability of belonging to the highest type. On the other hand, being a high school graduate increases the probability of belonging to type 1. In the simulated data 47.1% of the females belong to type 1 (low type), 26.7% belong to type 2 (medium type) and 26.2% belong to type 3 (high type). Types differ substantially across various dimensions. Preference parameters show that the marginal utility from sending their child to private school is positive for women belonging to the high type and negative for the low and medium type. Low and medium type women derive the highest utility from leisure but the lowest utility from higher child ability. Initial ability endowment of children born to low type women is more than 5 times lower than the initial endowment of children born to high type women. These differences persist as child ability evolves since mother's type also affects her productivity with the child.

[34] [57] found stronger results for Jewish women, who are more educated, on average, than non-Jewish women.

Increasing time with the child positively affects child ability for high type mothers, but has a negative effect for medium and low type mothers.

Women's latent type also affects the wage they earn. Estimates for the wage equation show that women belonging to the high type earn wages that are roughly 80 percent higher than wages earned by type 1 and 48 percent higher than wages earned by type 2. Husband's earnings are also affected by the woman's observed and unobserved characteristics, and capture positive assortative mating on woman's education level and type. The labor market returns for a man married to a low type woman are higher than a man married to a high and medium type woman, indicating negative assortative mating on latent type (assuming that men don't earn lower wages just because they are married to high type women, but there is in fact a correlation between the man's latent type and his wife's type which is being captured by the type parameters). Husband's earnings are also higher for women with a high school and more than a college degree, and lower for black individuals.

1.4.3.3 Goodness of Fit

I evaluate the model's ability to reproduce the life cycle wage profile and asset evolution observed in the data. These moments are not targeted directly in estimation, and provide an informal test of the model's ability to reproduce key data patterns from the data. Figure A.7 plots the results. Figure A.7 (a) shows that the model matches the average life cycle wage profile of women very well qualitatively.

Quantitatively, the model over-predicts wages in the first five periods. However, the concave profile of wages over time is well-matched by the model. Figure A.7 (b) shows asset accumulation over the life cycle in the data and model. The model matches the overall profile of assets over time very well.

In Table A.16 of Appendix A.4.2, I present results for the within sample fit of the simulated model to the life-cycle profile of females' work experience, private school choice, and the evolution of child ability. Results show that private school enrollment is slightly overestimated in the model, particularly for ages 6-11, however, the model does a good job of matching the ratio of private and public school students' cognition (as measured by test scores in the data) and the experience profiles of private and public school mothers. This shows that the model can reproduce key data features showing relative returns to private schooling and females' life cycle work decisions by child's schooling type.

1.5 Quantifying the Impact of Private Schooling

I now use the model to assess the impact of private schooling on female labor supply, asset accumulation, wages and its effect on child ability. I evaluate this impact by simulating life cycle outcomes under two scenarios. In the first scenario, I simply use the estimated parameters to simulate life cycle choices and outcomes for women and treat that as the baseline. Second, I simulate life cycle outcomes under the scenario in which preference shocks and all parameters associated with private schooling are set to zero. Under this scenario, no one chooses private schooling. I present differences in female's decisions for the two scenarios along various dimensions to quantify the impact of private schooling on key life cycle outcomes.

Time Allocation, Assets and Child Ability: Figure A.8 (a) plots the difference in employment rate over the life cycle between the two scenarios. Private schooling does not affect female labor supply in phase 1 (before child birth), however, there is a decrease, on average, in the employment rate of mothers of up to 1.4% when we shut down the private schooling channel, which suggests that after childbirth, particularly after the child starts school, private schooling induces women to work more.[35] Figure A.8 (b) shows that the decrease in employment is matched by an increase in the time mothers spend with their child, particularly at age 6, when the child starts school. In the absence of the choice to send your child to better quality private schooling, mothers choose instead to increase their time with the child on average.

As a result of the drop in annual hours worked and because women do not face the cost of private schooling in the future, thereby eliminating the precautionary saving motive, women accumulate lower assets over the life cycle, as shown in Figure A.8 (e). Lastly, Figure A.8 (f) shows how child ability will be affected under the no private

[35] There is also a decrease in women's labor supply in phases 2 and 3 at the intensive margin when the private schooling channel is shut down. Results for the intensive margin are available upon request.

schooling scenario. At age 6 and 7, child ability increases by 0.35%, primarily due to mothers spending more time with the child to compensate for the non-availability of good quality schooling. However, the positive impact of higher mother's time fades away and we observe a drop in child ability of up to approximately 0.2% at age 8 as the child ability is not augmented due to private schooling. Therefore, children graduate high school at age 18 with 0.1% lower child ability as measured by test scores, on average, than in a scenario in which private schooling was available.

Wages and Selection: Figure A.8 (e) plots the difference in log hourly wages (conditional on working) in the no private schooling scenario from the baseline scenario. On average, the hourly wage in the no private schooling scenario are higher than in the baseline scenario despite the overall decrease in work hours. This is because differences in wages represent differences in not just hours worked and accumulated experience, but also in the ability composition of women. Using the model, I can assess the role of private schooling in shaping the ability composition of working women over the life cycle. This adds to the literature on female labor supply that has evaluated the selection of women into the labor market [58, 59, 60, 61, 15]. Figure A.8 (f) plots the ratio of high ability (type 3) to low ability (type 1) women, conditional on working, for the no private school and baseline scenarios. Under the baseline scenario, at the time the child starts school, high ability women drop out of the labor force, with the largest drop from periods 9 to 14 (when the child is between 2 and 8 years of age). Shutting down the private schooling channel induces high ability women to rejoin the labor force during this time period, which shows that high ability women select out of the labor force if they send their child to private schools.[36] This selection of high ability (and education) women into the labor force when the private schooling channel is shut down also explains the overall increase in the average wage depicted in Figure A.8 (e).

Heterogeneity across Education: To explore the heterogeneous effect of private schooling on female's time allocation and asset accumulation, I plot females' life cycle outcomes across different education groups in Figure A.9. Figure A.9 (a) shows how asset accumulation differs between two scenarios across education groups. When we shut down private schooling, less educated women have lower net assets, with substantially larger effects for high school dropouts. On the other hand, women with some college or above have higher net assets in phase 3. This suggests that less educated mothers, particularly high school dropouts build up assets in response to a precautionary saving motive for private schooling. When the precautionary saving motive is shut down, they increase their consumption and accumulate less savings over their life cycle. On the other hand, more educated mothers use contemporaneous household income to pay for expensive private schooling. In the absence of private schooling, they save the money they were using to fund private schooling for their child.

The labor supply response by education groups is plotted in Figure A.9 (b). Figure

[36] Similar plot for college graduates versus high school dropouts is available upon request.

A.9 (b) shows that high school dropouts experience the biggest drop in employment rates starting at least two years before the child starts school when private schooling is shut down. In particular, employment rate of high school dropouts drops by up to 20% at the age the child starts school. On the other hand, there is an increase of up to 5% in employment rates of women with some college or above when the child starts school. These patterns suggest that the gap in labor supply observed before childbirth in Figures A.3 to A.4 was due to selection. However, after the birth of a child, and particularly when the child is above three years of age, women change their labor supply due to the decision to send their child to private schooling in the future. Consistent with Figure A.4 (a), the biggest drop in labor supply is observed for less educated women, who earn lower wages and also have lower non-labor income due to positive assortative mating on education. However, more educated mothers select out of the labor force when the child starts private primary school, as they are most productive with their time with the child, and also have higher non-labor income and savings to be able to afford private schooling. Lastly, Figure A.9 (c) shows how mothers belonging to different education groups change the amount of time they spend with their child when private schooling is not available. Mothers belonging to all education groups increase the amount of time they spend with their child, particularly when the child reaches school-going age. High school dropouts increase their time the most, which implies that they need to compensate the most in terms of time investment for the lack of availability of good quality schooling.

1.5.1 Causal Effect of a Change in p

I now calculate the causal effect of a change in private school tuition on private school enrollment as well as female's lifecycle choices and outcomes. Figure A.10 plots the elasticity of private school enrollment over different values of tuition. In line with estimates of private school elasticity in the literature, I estimate the private school elasticity to be -0.25 [62, 63]. However, using the model, I can calculate elasticity at different levels of private school fee. Results show that private school enrollment is more elastic at lower levels of fee, with a 1% increase in school fee leading to up to a 6% decrease in enrollment. At higher levels of fee, enrollment is less elastic. This suggests that parents who are sending their children to high cost private schools attach a higher valuation to private schooling (either due to higher returns or higher preference for private schooling) and are therefore less responsive to price increases.

Next, I study the impact of private school price decrease on female's and children's outcomes. Table A.6 shows that a 25% decrease in private school fee leads to a 7.7% increase in private school enrollment. The effect on other outcomes differs for incumbents (mothers who were already sending their children to private school) and new entrants (mothers who choose private schooling for the child after the price drop). The price drop pulls in children from the lower end of the ability distribution, who see large gains in ability once they move to good quality private schooling. New entrant mothers increase their labor supply as they now have to pay private school tuition. The increase in work hours translates to a 4% increase in terminal wages due to human capital accumulation over the life cycle. Terminal assets of these women also increase by 83% due to higher wage income. On the other hand, incumbents decrease their work hours by 1.4%, which leads to an average decrease of 0.1% in their terminal wages. However, these mothers are able to spend more time with the child, which leads to an overall increase in child ability of incumbent children. Moreover, due to the drop in tuition, mothers are able to accumulate higher assets over the life cycle.

In panel (b) of Table A.6, I report changes to life cycle outcomes when price decreases by 75%. As a result of the fee decrease, private school enrollment increases by 88%. Child ability increases for both the new entrants and incumbent since children are enrolled in good quality schools and mothers increase the time the spend with their children. The generous subsidy results in a decrease in work hours for new entrants. However, for incumbent mothers, we observe a 50% drop in hours worked, as they move from full-time work to part-time work. This leads to a substantial drop in the wages these women earn, as wages for this group decrease by 2.1%. Interestingly, terminal assets decrease for both groups of women. For new entrants, the anticipated fee subsidy diminishes the precautionary saving motive and leads to a 5.2% drop in accumulated assets. For incumbents, the drop in wage and the decrease in the precautionary saving motive due to lower school cost risk leads to a drop in terminal assets of 1.6%.

1.6 Assessing the Impact of Private School Subsidy

Private school vouchers have been one of the major education priorities of the new administration. The literature in the economics of education has mixed results on whether private school vouchers help improve academic achievement. While a number of studies have found positive effects of vouchers on student achievement [64, 65, 66, 67], recent studies on the Louisiana Scholarship Program have found negative effects [68, 69].[37] However, the literature on private schools has ignored an important spectrum of subsidizing child's schooling working through parental labor supply and asset accumulation. Moreover, policy initiatives such as providing subsidies for private schooling can have lasting impact on female labor supply and career trajectories. Insofar as private school subsidies in the form of vouchers will affect the incentive to work and save for parents, which will in turn affect the resources that parents can invest in their children, the link between vouchers and maternal labor supply and savings is an important area of study.

I compare the choices of women facing the baseline private school fee structure in the data with alternative hypothetical school fee structures that capture different subsidy schemes that can be designed for private schooling. The counterfactual highlights how changing the cost of private schooling affects not only private school enrollment

[37]A few papers have studied the political economy of private school vouchers [70, 71].

and student achievement, but also impacts female labor supply, labor market returns and asset accumulation. I analyze the effect of different subsidy schemes. First, I study the effect of subsidy programs which require households to pass an income test in order to qualify for the subsidy. Next, I analyze how life cycle outcomes are affected if targeted private school subsidies are given based on mother's education.

1.6.1 Subsidy with Asset Test

I conduct an experiment in which women get subsidies for private schooling for their child depending on the level of assets. The asset test requires that assets be less than 300% of the Federal Poverty Guideline. If households pass the asset test, they are eligible for a private school voucher capped at $6,100.[38] Results, reported in Table A.7 show that as a result of the subsidy, average private school enrollment increased by 56%. Overall terminal child ability increased by 0.3%, with terminal log ability of new entrants increasing by 1.03% while that of incumbents decreasing by 0.3%. The decrease in terminal log ability of incumbents can be explained by lower goods investment in children as incumbent mothers decrease their work hours, which decreases household income. The increase in child ability of new entrants is driven by access to better quality private schooling, as well as an increase in mother's active time with the child. I also find that mothers of new entrants increase their work hours, on average, by 24% in order to afford the additional cost of private schooling

[38]The cap is set at the average cost of private schools in the data.

net of the subsidy, however, due to the lower fee, incumbent mothers eligible for the subsidy are able to reduce their average annual hours by 21%. This results in terminal wage gains for mothers of new entrants but terminal wage losses of 30% for incumbent mothers.

Figure A.11 shows the distribution of assets at the time of child's entry into private schooling for the baseline and counterfactual with asset test. As a result of the asset test, mothers have lower accumulated assets at the time their child enrolls in private school.[39] However, Table A.7 shows that terminal assets, both for mothers of new entrants and incumbents, is higher than in the baseline. This implies that the subsidy allows women with low assets to enroll their children in private schools, and due to the subsidy, these women are able to accumulate more assets over the life cycle, and hence have higher terminal assets.

1.6.2 Targeted Subsidies to Different Education Groups

Private school subsidies can have heterogenous effects on student achievement and mothers' career paths for women belonging to different education groups. To explore these differences in responses and outcomes, I conduct an experiment in which I give a 25% subsidy to (a) only high school dropouts, (b) only high school graduates and (c) only to women with some college or higher. Table A.8 (a) shows that if women who are high school dropouts are given a subsidy to send their children to private

[39] The average assets at time of entry for the baseline is $16,467 while the average assets at time of entry under the counterfactual is $13,401.

school, overall private school enrollment increases by 3%. Child ability as measured by test scores goes up by 1.8% on average, and by 287% for new students who enter private schooling as a result of the subsidy. To afford private schooling, new entrants switch from unemployment or part-time work to full-time work, leading to an average 113% increase in hours worked. As a result of higher wage income over the life cycle, these women are also able to accumulate higher assets, with terminal assets 116% higher than in the baseline, and experience wage growth of 20%. On the other hand, there is a very small decrease in work hours of incumbent mothers, with no gains in child ability.

Next, in Table A.8 (b), I show that a 25% subsidy given to mothers with high school degrees leads to a 5% increase in private school enrollment. Decomposition analysis reveals that this leads to a 242% increase in child ability of new entrants, with no gains for incumbent children. New entrant mothers switch from part-time to full-time work to afford the cost of private school. This increase in work hours has dynamic effects on wages through the human capital accumulation channel, with terminal wages for this group of women 18% higher. Due to higher wage income, these women also accumulate higher assets over the life cycle, with terminal assets 32% higher than in a scenario with no subsidy. In contrast, incumbents mothers decrease labor supply by 0.4%, with no significant boost to child ability.

Lastly, in Table A.8 (c), I show the effects of a 25% subsidy to women belonging to the highest education group. A subsidy for this group results in only a 1% increase in private school enrollment. Among new entrants, terminal child ability increases by 1.11%, while there is no effect on ability of incumbent children. Due to the subsidy, new entrant mothers increase their work hours by 12.5%, suggesting that, on average, these women were at the margin of choosing private schooling for the child and can afford subsidized private schooling using their non-labor income and a very small increase in their labor supply. As a result of the subsidy, these women are able to accumulate higher assets, on average, with terminal assets 0.85% higher than in the baseline.

In summary, these results suggest that targeted subsidies to different education groups can substantially help women at the margin. The women who enroll their children into private schooling after the subsidy had low assets – for example, high school dropouts who were pulled into private schooling after the subsidy were up to $10,000 in debt on average. Therefore, these women were not able to make substantial goods investments in their children. Since the marginal productivity of their time with their child is low, they switch to working full-time and sending their child to private school once they are able to afford it after the subsidy. This increase in work hours positively affects their careers as well, since human capital accumulation over the life cycle leads to long term wage growth and higher asset accumulation. As expected, the magnitude of these effects are largest for the lowest education group. On the other hand, the subsidy acted as a windfall for incumbent mothers, with no returns in terms of child ability or wage growth for the mothers.

1.7 Summary and Conclusions

In this paper, I have focussed on the effect of the availability of private schooling on the trade-off that women face between working more to finance monetary investments in their children that augment child ability, or spend more time in child care activities at home. I developed a standard life cycle labor supply and savings model that allows for investment in children to quantify the role of private schooling in explaining labor supply and saving patterns of women with children. The results of the estimation showed that there is considerable observed and unobserved heterogeneity in who selects private schooling for their child, and that these systematic differences between individuals can also explain part of the differences in the observed labor supply patterns and effects of private schooling on child outcomes. For example, women without college degrees work more and accumulate savings to afford private schooling, while college educated women decrease their labor supply and spend time at home with the child if the child attends private school. Estimates of the child ability function showed that attending private school increases terminal ability by 7.8%, and that mother's time with the child and private schooling are complements. I also found that the private school enrollment is more elastic to price changes at lower levels of fee, and less elastic at higher levels of fee.

These complex interdependencies between female's work and savings choices and child's schooling imply that policies aimed at subsidizing private schooling can have effects beyond affecting student achievement. I illustrate that subsidizing private schooling for low income and low education women can result in large gains in children's outcomes for women at the margin. Moreover, private school subsidies can increase labor supply of new entrants, leading to long term wage growth. However, these subsidies act as windfalls for incumbent mothers, without any significant increase in child ability. The analysis in this paper suggests that evaluating policies only to the extent that they affect student achievement overlooks the impact of such policies on the entire household. The different subsidy schemes evaluated in the paper can be useful in designing subsidy programs that not only benefit children but also have positive impacts on female's career evolution and asset accumulation. Other policy reforms that can be evaluated using the model include giving subsidies declining in income. The model can also be used to evaluate which subsidy structure would maximize gain in child outcomes, holding constant total (new) government expenditures on subsidies.

This paper highlighted the connection between maternal labor supply and saving decisions and investment in private schooling. However, due to data constraints, I was not able to different types of private schools and the variation in their quality, that would affect not only child ability, but also mothers' valuation of private schools. Future research using detailed data that can distinguish between parochial non-sectarian schools would be more informative about the returns to private schooling, and its effect on female labor supply and savings.

Chapter 2

Housing Demand and Private Schooling

2.1 Introduction

What do we know about private schooling in the US? We know that its widely used - roughly 11% of all students in the United States (or about 5.4 million children) attend private school. Much research has examined its impacts, showing positive returns for students along a number of dimensions [28, 29, 30, 31, 32, 33, 34, 35]. However, private schooling is expensive, with costs ranging from \$5000 to up to

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$40,000 per annum. The high cost of private schooling implies that there must exist a strong correlation between private education and household income. However, it is difficult to establish a causal link between higher household wealth and investment in private schooling for the child.

The main challenge faced by researchers in attempting to identify a causal relationship between the two is the endogeneity of income. High-income households are more likely to be more educated and have higher latent productivity, which may be correlated with investments in children and preference for private schooling. To identify a causal link between household wealth and private school enrollment, I exploit the variation in the magnitude of the housing demand shock across MSAs in the US in the early 2000s. The identification strategy used in this paper is heavily influenced by the literature investigating the effects of the housing market boom on various aspects of the US economy.

Most of the research on this topic has focused on the effects of boom and the subsequent bust on macroeconomic outcomes such as the marginal propensity to consume and aggregate employment. The first evidence of the wealth effect of the house price boom and home equity extraction comes from [72], who show that an average homeowner borrows 25 to 30 cents for every dollar increase in home equity and that this borrowing is spent on real outlays rather than paying down debt or purchasing real estate. In a companion paper, [73] show that there is substantial geographical heterogeneity in the marginal propensity to consume out of housing wealth which can explain the heterogeneity in consumption across the same geographical regions.[1]

A separate literature has investigated how the housing market boom impacted employment opportunities for the workers living in areas which experienced the housing market boom. [78] and [79] exploit variation in local housing booms to show that it increased the employment opportunities for younger men and women and the workers impacted by the decline of manufacturing jobs. While laid-off manufacturing workers were able to change their sectors and gain employment in the housing sector, the boom also increased the opportunity cost of college for younger workers and college attendance declined in these areas. These papers also introduce a new identification strategy for analyzing the effects of the housing boom. Using models that identify sharp structural breaks in local housing prices, they show that the areas that experienced these sharp increases in housing prices had a plausibly exogenous variation in housing demand driven by speculative activity rather than by changes in the fundamentals of the local economy.

In the current paper, I borrow the identification strategy of [79] and [78] and apply it to the context of private school enrollment. In doing so, this paper also contributes to the literature that has analyzed the relationship between house prices and schooling. Typically this literature has focused on the effects of school performance and school quality on neighborhood housing valuations [36]. The consensus in this literature is that housing prices are significantly higher in places where measured

[1] Other papers in the literature using the geographical variation in the housing boom to analyze the effects on macroeconomic outcomes include [74], [75], [76] and [77].

school quality is higher (see [80] and [81] for a comprehensive review of the methods and results in this literature). Recent papers such as [82] have looked at publicly available data on value added generated by schools and have reached similar conclusions. None of the papers in this literature have looked at how house price increases can affect school choice and investment in human capital, which is the focus of the current paper.

There are two main channels through which a local housing demand shock can affect parents' schooling choice for their children. First, an increase in house prices should mechanically lead to higher property taxes, which are a source of revenue for local public schools. If higher revenue leads to higher expenditure per pupil and also translates to better public school quality, then private school enrollment may go down. On the other hand, increases in house prices may also lead to an increase in private school enrollment through two different channels. First, increases in house prices can relax liquidity constraints faced by households by allowing borrowing against higher home equity. This borrowing can be spent on children's education. The increase in household wealth can also lead to an increase in consumption in the absence of home equity extraction if it changes the marginal propensity to consume [83]. Secondly, an increase in house prices can stimulate the local economic activity in certain industries expanding employment opportunities for parents which can lead to higher income and spending on education including enrolling children in private schools. The net effect of a housing demand shock on private schooling will, therefore, be theoretically ambiguous, and will depend on the magnitude of the wealth effect relative to the effect of higher house prices on public school quality.

Using data from the Census, American Community Survey and Common Core Data, I find that a local housing demand shock during the early 2000s led to an increase in average total and current expenditure per pupil at public schools, however, it did not significantly change any observable measures of public school quality. One standard deviation larger housing demand shock in an MSA led to an 18% increase in private school enrollment in the MSA during the housing boom. This is consistent with results in the literature exploring the impact of housing wealth on college attendance. In the context of the housing boom of the early 2000s, [84] has documented that each $10,000 increase in housing wealth raised college enrollment by 0.7 percent. In a follow-up paper, [85], show that variation in house price increases in the housing boom also impacted the quality of college attended by students. They find that a $10,000 increase in housing wealth also increases the probability of enrolling in a public flagship university and the effects are higher in magnitude for lower-income students. These papers raised concerns that the subsequent housing bust and the decline in housing wealth could impact the enrollment in college education and subsequently the human capital of the next generation.

In my paper, I also explore how the housing bust in 2007 impacted private school enrollment. The housing bust would impact parents' schooling choice for their children through the same channels as a housing price increase. I find that private school enrollment decreased in MSAs that experienced a larger negative housing demand shock from 2006-2012. In terms of magnitude, a one standard deviation larger housing demand shock in an MSA led to a 17.4% decrease in private school enrollment in the MSA during the housing bust. These MSAs were the same MSAs that had experienced large house price gains over the period 2000-2006, a fact that has already been established by the existing literature, suggesting that over the entire period of 2000-2012 there were no changes in private school enrollment in these MSAs. This result is consistent with other research documenting symmetric effects of the housing boom and bust on different economic outcomes such as consumer spending [73], employment [74], college choices [78] and labor market outcomes [79].

The results in the paper also highlight the importance of credit constraints in investment in children. Existing literature has consistently found that credit constraints matter in human capital investment decisions [86]. [7] find that a $1,000 increase in income raises combined math and reading test scores by 6 percent of a standard deviation in the short run. In my paper, I don't focus on the impact of household income on student achievement, but do find a significant impact on parents' school choice. The results in the paper show that increase in household wealth and income affects parents' choices regarding children's schooling. These results show that relaxing credit constraints can lead to higher private school enrollment, and can be used to inform the debate on policies that aim to promote school choice.

2.2 Background, Data, and Descriptive Evidence

This section introduces the data set used in the analysis and presents descriptive statistics. First, I document national averages in private school enrollment and costs using data from the National Center for Education Statistics. Next, I present the various data sources used for the analysis, and show the relationship between the housing boom during the 2000s and private school enrollment in an MSA.

2.2.1 Private Schooling in the US

Data from the National Center for Education Statistics shows that private school enrollment in prekindergarten (preK) through grade 12 increased from 5.9 million students in 1995/96 to 6.3 million in 2001/02, and then declined to 5.4 million in 2013/14. Within grades, a higher percentage of students are enrolled in private schools offering Pre-K through grade 8 (12.8%) than in schools offering grades 9 through 12 (8.0%). Private schools are also a more popular choice in the Northeast, where 14% of all enrolled students went to private school, as compared to the West, where only 8.0% of all enrolled students went to private school in 2009.

Figure B.1 shows how the national average inflation-adjusted tuition has been evolving over since 1999-2000 school year for different types of private schools. The average tuition across all grades was $6,820 in the 1999-2000 school year and $10,940 in the 2011-2012 school year, which is an increase of around 60% in a little more than a decade. The bar chart also shows that the average tuition charged for all types of school has been increasing over the years, with the steepest rise for non-sectarian private schools. Schools associated with a religious congregation charge, on average, less than non-sectarian private schools. In the 2011-2012 school year, the cost of Catholic schooling was $7,020, as compared with $21,910 for non-sectarian private schools. Thus, not only are private schools charging a non-trivial amount, these costs have been rising at a higher rate than inflation in the past decade.

2.2.2 Data Sources

To investigate the impact of an increase in wealth on private school enrollment, I use data from two main sources. First, demographic characteristics, labor market variables and private school enrollment statistics at the MSA level are obtained from the 2000 Census and data from the American Community Survey (ACS). Second, MSA level information about public school supply and quality is constructed using the Common Core Data.

I obtain private school enrollment statistics and MSA level information on the share of females employed, the fraction of population that has a college degree, proportion of African-Americans, proportion of people living below the poverty line, median household income and total population of school-going children from the Census and multiple years of the ACS. The relevant years for the analysis are years 2000, 2006 and 2012. The year 2000 marks the start of the housing boom in the US, the year 2006 marks the end of the housing boom and start of the housing bust while the year 2012 marks the end of the housing bust. The variable of interest is how private school enrollment has changed during the boom period (i.e. between 2000 and 2006), and how it evolved over the housing bust (between 2006 and 2012). The private school enrollment at the MSA is calculated as the proportion of school-going children between the ages of 3 to 17 who were attending private school.[2,3]

MSA-level averages for all variables for the year 2000 are constructed using the 2000 Census. However, to compute averages for the years 2006 and 2012, I use multiple years of the ACS to increase the sample size and precision of the estimates. In particular, I pool ACS data from the year 2005 to 2007 to construct averages for the 2006 period and pool ACS data from the year 2011 to 2013 to construct averages for the 2012 period.[4] The Census/ACS sample is restricted to include school-going children, not living in group quarters, who are residing in an MSA in their state of birth. Imposing the restriction of children residing in an MSA in their state of birth partially alleviates concerns about the results being confounded by endogenous migration across states by parents of these children in response to local labor demand and school supply shocks.

[2] The denominator for this proportion excludes children who were home-schooled. Children between the ages of 3-5 were attending pre-school.

[3] I topcoded the private school enrollment variable at the 95^{th} percentile to eliminate outliers.

[4] For all years except 2012 and 2013, I use the METAREA variable from IPUMS to identify MSAs. For the years 2012 and 2013, I use the variable MET2013, which I match to METAREA by hand, so that it is possible to pool the 2011-2013 datasets.

A key component of this paper is to use the housing demand shock during the 2000s to isolate the effect of an increase in household wealth and income on private school enrollment. I use the measure of local housing demand shocks created in [78], in which the local housing demand shock is a function of the change in local housing prices and change in the quantity of local housing available. Local housing prices are obtained from the Federal Housing Finance Agency (FHFA) annual series on prices in FHFA metro areas.[5] Local housing supply is proxied by the number of new privately owned housing units authorized via permits, data on which is obtained from the Census Building Permits Survey.

Lastly, I construct measures of local public school supply and quality using Common Core Data. The Common Core Data (CCD) is the Department of Education's primary database on public elementary and secondary education in the US. It is a comprehensive, annual, national database of all public elementary and secondary schools and school districts. Among other things, it collects information about the number of schools, by public school type, number of teachers, by grade, number of students, by race, at the school and school district level. I use the CCD to construct measures of total number of public schools, student-teacher ratio, current spending per pupil, total spending per pupil and proportion of free lunch students at public schools at the county level. I then use a county to MSA crosswalk to match CCD

[5] Data from FHFA is matched directly to Census/ACS data using MSA code as the unique identifier. There were 15 MSAs within the Census data that did not map directly to any MSA within the FHFA data. For these 15 MSAs, I use matched data from [78], who manually map these 15 Census MSAs to FHFA data.

averages to the Census/ACS MSAs.

I also include a measure of the average private school tuition at the state level to control for differences in price of private schooling. State level tuition data is obtained from `privateschoolreview.com`, a website that lists private schools in each state, gives information about the average tuition at the state and national level, as well as information on average acceptance rates, student body demographics and teacher student ratios. The website also hosts articles for parents on why they should send their child to private schools, and if they choose to do so, how they can pay for it. Data on tuition is available at the state level only for the school year 2014-2015. I extrapolate data for my sample years and adjust the fee data by inflation.

2.2.3 Theoretical Discussion

Theoretically, if private schooling investment for the child is a normal good, both changes in housing prices and changes in housing supply can affect private school enrollment through their affect on household wealth and their impact on employment opportunities for parents. The housing supply channel can increase the volume of housing transactions which stimulates sectors associated with the selling and financing of housing (e.g., mortgage brokers, real estate agents, etc.), which can possibly boost parental employment working in these sectors and lead to an increase in private school enrollment.

Increase in housing prices can stimulate investment in private schooling either through a housing wealth effect, or by relaxing liquidity constraints. In the aftermath of the housing boom and the subsequent bust, a growing literature has argued that house price movements can have large effects on consumption. Most of the research on this topic has focused on the effects of boom and the subsequent bust on macroeconomic outcomes such as the marginal propensity to consume and aggregate employment. The first evidence of the wealth effect of the house price boom and home equity extraction comes from [72], who show that an average homeowner borrows 25 to 30 cents for every dollar increase in home equity and that this borrowing is spent on real outlays rather than paying down debt or purchasing real estate. In a companion paper, [73] show that there is substantial geographical heterogeneity in the marginal propensity to consume out of housing wealth which can explain the heterogeneity in consumption across the same geographical regions. They find that, the non-durable consumption elasticity out of housing wealth is between 0.13 and 0.25[6] Other recent papers such as [76] and [75] arrive at similar numbers using different data sources and identification strategies. Relaxation of liquidity constraints and housing wealth effect on consumer spending can also stimulate local labor market opportunities as shown in [74], which can therefore increase private school enrollment as parents earn higher wage income.

Such a large consumption effect out of housing wealth was thought to be at odds with the theoretical models of housing consumption such as [87]. Such models would

[6] see the discussion in [83] on how this estimate was calculated.

argue that increases in the value of an individual's house are offset by increases in future implicit rental costs, leaving the expected lifetime budget constraint unchanged. Hence, if households make consumption decisions based the net present value of future wealth, then the consumption effects out of housing wealth will be small. However, recent papers in the macroeconomic literature such as [83] have shown that such large effects can be rationalized in models with incomplete asset markets where agents are facing liquidity constraints. Similar arguments would imply that housing wealth increases can have impacts on educational spending and consequently private school enrollment. There is also evidence that the Marginal Propensity to Consume out of transitory income shocks changes over the business cycle [88] backed by theoretical models of consumption [89], which could imply differential responses to private school enrollment over the business cycle or the housing boom and bust.

Another important channel through which a local housing demand shock, in particular, an increase in house prices, will affect parents' propensity to send their children to private schooling is by affecting the quality of local public schools. An increase in house prices will naturally lead to higher local property taxes, which are an important source of funding for local public schools. If higher revenue streams from higher property taxes translate into better public school quality, parents should be less likely to enroll their children into private school as the quality of public school has improved. Therefore, the overall effect of a local housing demand shock on private schooling is ambiguous, and depends on the magnitude of the income effect and the effect on public school quality.

2.2.4 Private School Enrollment and Local Housing Demand Shock

Table B.1 presents descriptive statistics for private school enrollment during the period of analysis. In the year 2000 average private school enrollment in the US was 9.03%. It increased to 9.32% in 2006 and decreased to 8.90% in the year 2012. The average change in private school enrollment between 2000-2006 was 0.26% and -0.46% between 2006-2012. Figure B.3 plots the distribution of the change in private school enrollment during these time periods. The histograms show that a greater density of MSAs have a positive change in enrollment between 2000-2006, while a greater density of MSAs have a negative change in enrollment between 2006-2012.

I use the measure of local housing demand shocks constructed in [78] to quantify the relationship between wealth increases and private school enrollment. A local housing demand shock, ΔH_k^D, produces both a change in house prices and housing quantity, given by:

$$\Delta H_k^D = \eta_k^D \Delta P_k + \Delta Q_k \tag{2.1}$$

where ΔP_k is the change in log local housing prices in MSA k, η_k^D is the price elasticity of housing demand, and ΔQ_k is the change in log local housing supply. Existing literature estimates the price elasticity of housing demand to approximately equal 1

[90, 91], therefore, the change in housing demand over any two periods, $\widehat{\Delta H_k^D}$ can be proxied by the sum of a change in log housing prices and change in log of new housing produced in the MSA over the two periods. Table B.1, panel (b) presents summary statistics of the local housing demand measure. The average house price index grew from 0.72 in 2000 to 1.07 in 2006. During the 2000-2006 period, house prices grew by 33% on average, while housing supply grew by 21% on average. The average local housing demand shock between 2000-2006 was 54%, which captures both a change in local housing prices and change in local housing supply.

Table B.2 shows how the labor market performed during the sample years. Panel a) shows the employment industrial mix across MSAs in the year 2000. Almost a quarter of the US population was employed in manufacturing and construction sector at the beginning of the decade. As documented by [79], the employment in the Construction and FIRE sectors increased during the 2000-2006 housing boom period which masked the decline in Manufacturing employment over the same time period. The inflation-adjusted average hourly wage for males in an MSA in 2000 was $12.1 while that for females was $10.3.

Panel b) and Panel c) show the changes in the labor market outcomes of male and female workers over the boom and bust period respectively. On average, male and female annual real wage income declined in both the boom and the bust period with the average decline being 4 times larger over the bust. The panels also show that male labor force participation increased by 0.19% over the period 2000-2006 while it decreased by 0.68% over the 2006-2012 period. On the other hand female labor force participation declined in both time periods, with the bigger decline being in the 2006-2012 period. Employment rates declined for both groups over the 2000-2012 period, although the decline was not as high as the decline in the labor force participation rate.

To explore the relationship between the local housing demand shock and local public school quality, I estimate first-difference regressions of the form:

$$\Delta Y_{kt}^{pub} = \beta_0 + \beta_1 \widehat{\Delta H_{kt}^{D}} + X_{kt}\boldsymbol{\beta} + \epsilon_{kt} \tag{2.2}$$

where $\widehat{\Delta H_{kt}^{D}}$ is the change in local housing demand, while ΔY_{kt}^{pub} is the change in public school quality measures in MSA k between time periods t and $t+s$. The first difference specification eliminates any latent MSA-specific factors that remain fixed over time. I also include a vector of controls X_{kt}, which control for any dimensions in which MSAs might systematically differ from each other and can also affect public school quality. The vector includes controls for the share of college graduates in the MSA, share of employed females, proportion of African-Americans, proportion of people living below the poverty line, the median household income in the MSA and the population of school-going children in the MSA in 2000. I also control for differences in local labor markets across MSAs in 2000s by including controls for the percentage of individuals in an MSA employed in construction, manufacturing, FIRE industries, wholesale trade, retail trade and transportation, as well as the average hourly wage earned by men and women. These measures capture the idea that variation in the industry mix in an area is correlated with demographics that affect schooling choice, as well as the response to the housing demand shock. Standard errors in all regressions are clustered by state and the regressions are weighted by the population of children in the year 2000.

Table B.3 shows how the local housing demand shock between 2000-2006 affected current expenditure per pupil, total expenditure per pupil, student-teacher ratios and proportion of free lunch students in public schools in an MSA. A 100 log point increase in the local housing demand shock between 2000-2006 raised current and total expenditure per pupil by 4 percentage points. This is not surprising, since the housing demand shock should increase public school revenue, which translates to higher expenditure per pupil. Column (3) of Table B.3 shows that a 100 log point larger housing demand shock between 2000-2006 predicts that average student-teacher ratio in the MSA would go down by 1.05 unit, however, there is no significant effect on the proportion of free lunch students in an MSA.

Results in Table B.3 suggest a correlation between the housing demand shock between 2000-2006 and public school inputs. To explore how the local housing demand shock relates to local private school enrollment I run first-difference regressions of the form:

$$\Delta P_{kt} = \alpha_0 + \alpha_1 \widehat{\Delta H_{kt}^D} + X_{kt}\boldsymbol{\alpha} + \mu_{kt} \tag{2.3}$$

where ΔP_{kt} is the change in mean private school enrollment in MSA k between time periods t and $t+s$. In addition to MSA level demographic and labor market controls, I also control for the total number of public schools, student-teacher ratio, log current expenditure per pupil and proportion of free lunch students at public schools in the MSA in the year 2000 to account for differences across MSAs in public school quality, which would directly affect parents' decision to enroll their children into private schooling. Table B.4 shows that the local housing demand shock does not predict any increase private school enrollment during 2000-2006. However, one reason why the OLS estimates are biased towards zero is measurement error in the construction of the local housing demand shock. The data suffers from measurement error in prices, permits and dating of the start and end of the boom period in an MSA. There is randomness and measurement error in the housing demand variable in each year, and I am not using all years from 2000-2006 to smooth out the trend.

2.3 Econometric Model

In order to identify a causal relationship between the housing demand shock and private school enrollment, we need to isolate exogenous changes in housing demand. A potential challenge to identifying the causal effect of changes in local housing demand on any kind of local outcome is that these demand changes might be correlated with latent MSA factors such as latent amenity shocks, labor demand shocks and labor supply shocks. Such factors and changes could affect the type of schooling chosen for children either directly or indirectly through the change in demographics and income of the local population. This would cause a bias in the OLS estimates.

I use the instrument created in [78] to isolate exogenous variation in local housing demand. The [78] strategy for isolating exogenous variation in housing demand changes relies upon the emerging consensus in the literature that changes in housing prices, production and transactions during the housing boom and bust in the U.S. was caused primarily due to a speculative 'bubble' [78, 92, 93, 94], and not due to changes in construction costs, latent productivity, incomes and population.

To create their instrument, [78] search for rapid changes in local housing prices that occurred between 2000 and 2006. The identifying assumption behind using rapid increases in housing prices is that underlying fundamentals at the MSA level will not change abruptly and the changes will be smoothly incorporated in house prices. However, sharp breaks from the trend in housing prices may arguably be a result of speculative activity or other housing specific activity, rather than changes in latent MSA specific factors - such as public school quality, among other things - that will be correlated with private school enrollment and be a source of endogeneity in our OLS estimates. Such variation in the timing of boom across US MSAs has also been documented by [95].

In order to further explain the identifying variation coming from this instrument, consider two hypothetical MSAs that have a similar increase in house prices over the period 2000-2006. However, one MSA experiences a ”smooth” increase in prices over that time period indicating that there were latent changes in the MSA that were gradually incorporated into increases in house prices over that time period. In contrast, the other MSA has a sharp jump in house prices at a given point in time between 2000-2006 rather than a ”smooth” evolution implying that the increase was driven by ”speculative activity” rather than by changes in latent fundamentals affecting house prices. In their paper, [79], provide examples of both types of MSAs. MSAs that fit the ”smooth” price increase pattern and include Pittsburgh, Chicago and New Haven whereas MSAs that fit the latter pattern include Portland, Tuscon and Naples. We would expect the latter MSAs to have experienced changes in housing demand that were orthogonal to local fundamentals and hence unrelated to local economic activity.

2.3.1 Structural Break in Local Housing Prices

To create the instrument variable [78] use quarterly price series data from each MSA in the sample between 2000Q1 and 2005Q4, and estimate MSA-specific OLS regressions with a single structural break. Following the time series econometrics literature for estimating structural breaks with unknown break dates [96, 97], they search for the location of the break that maximizes the R^2 of the following regression:

$$HP_k(t) = \omega_k + \tau_k t + \pi_k(t - t_k^*)\mathbf{1}\{t > t_k^*\} + \xi_{k,t} \tag{2.4}$$

where $HP_k(t)$ is the log local housing price in MSA k in year-quarter t, t_k^* is the date of the structural break in the MSA's time series, restricted to be between 20001Q1 and 2005Q1, τ_k is an MSA-specific linear time trend before the structural break and π_k measures the extent to which the growth rate of MSA's quarterly house price series changed at the break. For MSAs that experienced no break from the linear trend in house prices, the estimate of π_k would be close to zero.

Figure B.2 maps the variation in the magnitude of the structural break in house prices across MSAs in the US. This is the variation that will be exploited to identify a causal effect of the housing demand shock on private school enrollment. As the map shows, MSAs such as Yuma, Arizona and Naples, Florida experience a large change in house prices during 2000-2005. On the other hand, MSAs such as Bloomington, Indiana, and Eau Claire, Wisconsin experienced very small deviations from the linear trend in house prices.

2.3.2 Instrument Relevance and Validity

Table B.5 shows the correlation between the magnitude of the structural break in house prices between 2000-2006 and housing demand shocks during the boom and bust. The housing demand shock during 2000-2006 has a strong positive correlation of 0.70 with the structural break while the housing demand shock during 2006-2012 has a strong negative correlation of -0.6 with the structural break in house prices between 2000-2006. The housing demand shock during the boom and bust are also negatively correlated, which is consistent with the idea that the MSAs that faced the biggest increases in house prices during the boom also faced the biggest crash during the housing bust. Figure B.4 (a) shows that the magnitude of the structural break strongly predicts the local housing demand shock between 2000 and 2006 period, with the instrument variable explaining 53% of the variation in the local housing demand shock between 2000 and 2006. Figure B.4 (b) shows that the structural break in house prices between 2000-2006 also strongly predict the negative housing demand shock during 2006 and 2012, a fact I exploit to study the effect of the housing bust on private school enrollment between 2006-2012.

Table B.6 shows the first stage relationship between the magnitude of the structural break in house prices and the 2000-2006 change in the local housing demand measure, local housing prices and local supply of housing. In these first stage regressions, I control for a host of MSA-level variables to account for underlying differences across MSAs in the year 2000. For each of the regressions, even after including MSA-specific controls, the structural break strongly predicts the local housing demand shock and the increase in housing prices and housing supply. The F-statistic in all three regressions is greater than 20, eliminating any concerns about the estimated structural break being a weak instrument. To show that the estimated structural break is a valid instrument, [78] present evidence that the structural breaks capture exogenous speculative activity in the area. They show that the price/rent ratio in an MSA is positively related to the magnitude of the structural break, which shows that the price of owning rose relative to the price paid by renters, suggesting that the structural break is picking up investors' positive judgement above the future desirability of an MSA. [78] also use data on out-of-town buyers in an MSA to show that there is a strong correlation between the structural break and the growth in the share of speculative out-of-town buyers.

Figure B.5 explores whether the estimated structural breaks are reflecting variation in public school quality across MSAs, which would affect school choice. The identifying assumption behind the instrument is that it should be orthogonal to any factors that would drive educational choices for children. Figures B.5 (a) and (b) show that total expenditure per pupil and total supply of public schools in an MSA in the year 2000 are uncorrelated with the magnitude of the structural break.

In Figure B.6, I explore the relationship between the structural break and MSA-level demographic controls that may also predict private school enrollment. These controls include the proportion of African-Americans, share of college-educated individuals, proportion of people living below the poverty line and the share of working women in an MSA in the baseline year 2000. Other than the proportion of African-Americans in an MSA in 2000, which is negatively correlated with the magnitude of the structural break, all other underlying MSA characteristics are uncorrelated with the instrument variable. These figures lend support to the instrument validity argument, allaying concerns that the structural break are just capturing observable variation across MSAs that are correlated with children's school choice.

2.4 Results

Using the Census/ACS sample and the estimated structural breaks, I estimate first-difference regressions specified in equations 2.2 and 2.3, instrumenting $\widehat{\Delta H^D_{kt}}$ with the magnitude of the structural break in the MSA.

2.4.1 Housing Boom and Schooling Choices

I first investigate whether the exogenous increase in house prices led to a significant increase in public school spending and observable measures of quality. The first two columns of Table B.7 show that an exogenous increase in house prices leads to a significant increase in the current and total expenditure per pupil in public schools. This is not surprising, because even if house prices increase due to speculative activity, public school revenue must increase, which translates to higher spending per pupil. Columns (3) and (4) show that despite higher funding, the student/teacher ratios and proportion of free lunch students in public schools did not change during the 2000-2006 period[7] This is consistent with existing literature in the economics of education that shows that throwing money at schools does not improve student achievement [98, 99, 100, 101].

These results show that the housing demand shock did not perceivably make public schools more attractive to parents in the time period between 2000-2006, which

[7]Another tangible measure of public school quality is average school test scores. However, the Common Core Data does not collect standardized test score data.

could have potentially led to a drop in private school enrollment. The second channel through which a local housing demand shock could affect parents' schooling choices for their children is by affecting their budget constraint, either through higher wage income or by relaxing liquidity constraints. I control for MSA-specific demographics, local labor market variables, public school quality measures and an index for the average private school tuition in the area. Table B.8 shows that in an MSA experiencing a 100 log point larger increase in housing demand between 2000 and 2006, average private school enrollment was 3 percentage points higher. The result is highly statistically significant, even after adding all controls. The average private school enrollment in the year 2000 was 9.03%, which implies that a 100 log point larger increase in housing demand in an MSA led to a 33% increase in private school enrollment, on average. A one standard deviation change in the local housing demand shock during the 2000-2006 period was 0.54, therefore, using the estimates we can conclude that a one standard deviation change in the housing demand shock was associated with an 17.9% increase in private school enrollment in that MSA.

2.4.2 Housing Bust and Private School Enrollment

The substantial increase in private school enrollment during the housing boom shows the importance of credit constraints affecting investment in children. This also shows that parents consider private schooling to be a normal good, as its consumption increases with an increase in income. In this section, I examine how private school enrollment changed during the housing bust during 2006 - 2012. The housing bust resulted in people losing housing values as well as lower employment opportunities and wage incomes. Therefore, it is possible that private school enrollment may decrease as a result of the negative local housing demand shock. As previously shown, the housing demand shock during 2000 - 2006 has a strong negative correlation with the housing demand shock during the bust. Therefore, to identify a causal effect of the negative local housing demand shock, I estimate first-difference models relating private school enrollment during 2006-2012 to the 2000-2006 change in local housing demand. The TSLS regressions are estimated using the magnitude of the structural break in house prices during 2000-2006 as an instrument for the change in housing demand. The regression also controls for MSA-specific demographics, public school quality measures and local labor market controls for the year 2000.

Table B.9, column (1) shows that an MSA experiencing a 100 log point larger increase in housing demand during 2000 - 2006 experienced a 3 percentage point decrease in private school enrollment during the housing bust. The estimate suggests that when credit constraints tighten, parents substitute at the margin of children's school choice, with private school enrollment decreasing by 32% between 2006 and 2012. The second column of Table B.9 shows how private school enrollment evolved during the full cycle from 2000 - 2012. As expected, the overall change in private school enrollment from 2000 - 2012 was zero, since the increase in enrollment during the boom was exactly counteracted by the decrease in enrollment during the bust.

2.4.3 Mechanisms

In Table B.10, I explore whether the effect of the local housing demand shock was different across MSAs with different housing supply elasticities, which helps in decomposing the effect of the housing demand shock into the effect coming from a change in housing prices and changes in housing supply. If the effect of the local housing demand shock on private school enrollment was primarily driven by increases in employment opportunities of parents only in construction related occupations, we would expect the effect of the housing demand shock to be positive and significant in MSAs where housing supply was more elastic. I use housing supply elasticity estimates from [102] and interact them with the local housing demand measure in 2000-2006 to test this hypothesis.[8] Results show that the local housing demand shock did not have differential effects on private school enrollment in MSAs where housing was inelastically supplied relative to MSAs where housing was elastically supplied. This suggests that the effect of the local housing demand shock on private school enrollment was driven by house price increases, which relaxed liquidity constraints for parents, as well as increased employment opportunities by fueling consumption.

To further understand how the housing boom of 2000-2006 affected employment opportunities of parents of school-going children, I run first-difference regressions relating fathers' and mothers' employment and wage income to the 2000-2006 local housing demand shock. Table B.11 and B.12 show how the labor market outcomes for

[8] I lose observations on 24 MSAs when matching Saiz elasticity estimates with data from the Census/ACS.

mothers and fathers of children of school-going age responded to the housing boom. A 100 log point larger increase in the local housing demand increases fathers' labor force participation by 5 percentage points and their annual wage income by 22%. Table B.12 shows that the housing boom did not significantly affect mothers' labor force participation or wage income, however, it led to a 2 percentage point increase in females' employment rate. These results show that one of the channels through which the housing boom increased private school enrollment was by increasing employment opportunities for parents, that eventually led to higher labor income that could be spent on private school tuition. I also see how non-labor income, defined as family income minus any wage income earned by parents, was affected by the local housing demand shock. I find that a 100 log point larger increase in the local housing demand shock increased family's non-labor income by 23%.

Similarly, Tables B.13 and B.14 show that a 100 log point larger increase in the local housing demand shock during 2000-2006 led to a 7 percentage point decrease in father's labor force participation, 3 percentage point decrease in mothers' labor force participation, a 25% decrease in fathers' annual wage income and a 12% decrease in the annual wage income earned by mothers. This shows that MSAs that experienced the largest housing boom during the early 2000s saw large declines in parents' employment opportunities during the bust, which led to lower income that could be used to pay for private school tuition.

2.5 Conclusion

In this paper, I assess the relationship between the housing demand shocks and parents' investment in private schooling for their children. I focus on the housing boom of the 2000s and investigate the channels through which a positive local housing demand shock can affect schooling choice. The measure of housing demand shock I use in the paper is borrowed from [78], in which the local housing demand is a function of an increase in both housing prices and housing supply. An increase in housing prices will mechanically increase public school revenue generation through higher property taxes, and can potentially make public schools a more attractive choice for parents if higher expenditure also results in higher observable public school quality. On the other hand, a positive housing demand shock also leads to a relaxation of liquidity constraints and increases employment opportunities for parents, which can both lead to higher income. If private schooling is a normal good, then due to a pure income effect, we would expect to see an increase in private school enrollment.

To isolate the causal effect of the local housing demand shock on private school enrollment, I exploit the exogenous variation in the growth in house prices across MSAs during the 2000s which was orthogonal to the latent underlying characteristics of an MSA [78]. I find that the local housing demand shock during the early 2000s led to an increase in the total expenditure per pupil in public schools, however, it did not result in significant changes in the average student/teacher ratios at public schools, which suggests that perceived public school quality did not improve. Results for private schooling enrollment show that a one standard deviation larger increase in the housing demand shock during the 2000-2006 period in an MSA led to a 18% increase in average private school enrollment in that MSA. Similar analysis during the housing bust period extending from 2007-2012 shows that the increase in enrollment was completely counteracted by an equal decrease in private school enrollment during the housing bust. Using data on parents' labor market outcomes, I show that the mechanism through which the housing demand shock affects private school enrollment is by increasing parents' employment opportunities and earned income.

These results underscore the importance of relaxing credit constraints to promote quality investments in children. The estimates for private school enrollment during the housing boom can be interpreted as the elasticity of private schooling with respect to household wealth, specifically coming through the housing market. We learn that private schooling is a normal good, with higher household income leading to an increase in average private school enrollment, and a decrease in household wealth leading to a decline in private school enrollment. These results imply that by relaxing credit constraints for private schooling, the housing boom of the 2000s could have long-run impacts on the human capital of the children of the boom. Future work should trace how academic achievement and long-run education and labor market outcomes of these children were affected. Given that private school enrollment has been shown to have positive effects on childrens' achievement along a number of dimensions, another important question for further exploration is whether being born just before a boom versus just before a bust leads to long-run inequality in outcomes.

Chapter 3

Positively Aware? Conflicting Expert Reviews and Demand for Medical Treatment

This chapter is joint work with Nicholas W. Papageorge and Jorge Balat.

3.1 Introduction

Consumers facing uncertainty often turn to low-cost sources of information, such as word-of-mouth, advertisements or product reviews generated by other consumers

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or by experts. In the case of expert reviews, the idea is that individuals turn to a trusted or authoritative information source to help them make decisions. Previous research has demonstrated that expert reviews help drive demand for a number of products, such as movies, wine and books. The impact of expert reviews also extends to higher-stakes contexts, such as financial decisions [103, 104, 105, 106].[1]

Despite the importance of expert reviews in several economic contexts, little is known about how consumer demand responds to conflicting expert reviews. Yet, consumers often have access to multiple reviews from different experts who potentially disagree. One possibility, which we explore in this paper, is that individuals facing conflicting reviews rely upon expertise from the source they view as best aligned to their preferences. Seen this way, individuals facing uncertainty are not passive consumers of available information, but instead appear to actively choose which information source to incorporate into their decisions.

In this paper, we study the impact of expert reviews on the demand for HIV drugs.[2] In our setting, consumers face uncertainty about drug qualities, including treatment efficacy and adverse treatment side effects. Their choices affect their health, well-being and survival. At multiple points in its lifecycle, each HIV drug we study is reviewed by both an HIV physician and an HIV activist, the latter often someone infected with HIV. We demonstrate that favorable expert reviews increase demand for HIV

[1] [107] show evidence that social information affects decisions in high-stakes contexts, in their case, career choices.

[2] HIV stands for Human Immunodeficiency Virus, which is a virus that attacks the immune system.

drugs. This finding provides evidence that the influence of expert reviews extends to long-run health investments. Next, we examine patient responses to conflicting reviews, i.e., when the doctor and activist disagree about a given drug. In such cases, consumer responses vary by their current health, with sicker consumers choosing treatments recommended by the doctor and healthier consumers following the activist. To explain this pattern, we argue that consumer responses to expert reviews depend on their incentives to use effective treatments despite adverse side effects — and that these incentives shift with health status.

Examining consumer responses to conflicting reviews requires data that are often lacking in studies linking expert reviews to demand. To study HIV drug reviews and demand, we merge two unique data sets. The first is from a longitudinal study of men infected with HIV (henceforth, HIV-positive or HIV+), which provides detailed information on a variety of health measures and also records each individual's medical treatment consumption decisions. Using this data set, we can relate patient health outcomes to the treatments they use, which allows us to construct two objective treatment characteristics: a measure of treatment effectiveness against HIV and a measure of treatment side effects. We merge this information with a data set consisting of manually-coded drug reviews. Doctor and activist reviews are disseminated in a comprehensive HIV drug guide published annually in a widely circulated HIV lifestyle magazine called *Positively Aware*. As we explain in detail below, text reviews are scored as positive, negative or mixed.[3] By combining these two data sets, we are able to relate potentially conflicting activist and doctor reviews to drug demand and health outcomes. Moreover, since we observe objective product qualities, we not only control for them, but also relate them to reviews to better understand how reviews are generated and, in particular, why doctors and activists sometimes disagree about a given drug. Observed objective qualities are also integral to our identification strategy in a way to be explained below.

We present two main sets of results. First, we estimate a discrete choice model of demand for HIV drugs and provide arguably causal evidence that positive reviews increase demand for HIV drugs. A positive correlation between positive reviews and high demand could be driven by omitted third factors, such as unobserved drug qualities, which affect both reviews and demand. We overcome potential endogeneity problems by exploiting rich data on objective product qualities along with repeated reviews of the same drug over time. Our identification strategy relies on the idea that as new drugs emerge, reviews for existing drugs shift in response. Thus, we can use the objective qualities of rival drugs on the market, which change over time as the market evolves, to instrument for reviews. Our identification strategy follows the spirit of [108] (henceforth, BLP), as we exploit characteristics of a shifting set of rival products on the market to instrument for a drug's review.[4] Estimates indicate that

[3]Drug reviews from *Positively Aware* also contain information on a host of additional drug characteristics, including known interactions, dosage and number of side effects discovered during clinical trials, information which we also use in our empirical analysis.

[4]While we do not model the process by which reviews are generated, we maintain the identification assumption that the entry of new drugs is orthogonal to the unobserved characteristics of existing

reviews have a positive impact on demand. In particular, if reviews for a treatment increase from neutral to positive, the average probability of taking it increases by 1.8%. To put this into context, an equivalent impact on demand would occur if drug effectiveness (measured by the probability that patient CD4 count rises within six months) improved by roughly 2%.

Our second set of results focuses on explaining consumer demand responses to conflicting reviews.[5] We find that, when the reviews of doctors and activists diverge, relatively healthy patients follow the activist rather than the doctor. Our preferred explanation is that this behavior is driven by patient distaste for drug side effects. To support this view, we provide three pieces of empirical evidence. First, we show that doctor and activist disagreements arise when a treatment is highly effective but has severe side effects, in which case it is given a lower review by the activist, but not by the doctor.[6] If patients favor drugs with fewer side effects and face diverging reviews, they might choose to follow the expert — in this case an HIV activist who is also a fellow patient — who tends to downgrade drugs with harsher side effects. Second, using rich data on individual health characteristics, we show that consumer demand responses lead to declines in health along with reductions in side effects. This would likewise be expected if consumers follow activist reviews in an effort to

drugs.

[5]As reviews are printed on the same page, one after the other, in the same magazine, the presumption is that individuals are exposed to both.

[6]This is in line with research demonstrating that doctors care less about side effects than patients do. In a particularly striking contribution, [109] show that doctors, when they fall ill, avoid drugs with side effects despite having recommended them to their patients.

avoid effective drugs with harsh side effects. Third, we examine demand responses of HIV+ men who are relatively sick (a condition known as AIDS).[7] Previous research has shown that patients who choose less effective treatments to avoid side effects are more willing to choose effective treatments with adverse side effects when in poor health since the payoff from doing so in terms of improved health is large [110]. This suggests a way to test the validity of our preferred explanation. The reasoning is that if healthier consumers follow the activist in an effort to avoid side effects, we would expect sicker patients to respond more positively to the doctor, the expert who tends to recommend highly effective treatments despite adverse side effects.[8] Indeed, we find that, in contrast to healthier patients, sicker HIV+ men respond positively to higher doctor reviews. Together, these findings provide support for the idea that patients choosing HIV treatments under uncertainty utilize information from the expert they view as best aligned to their preferences, which can vary by health status.

This paper contributes to several strands of literature in economics. The first studies how individuals facing uncertainty rely on a variety of information sources, such as direct-to-consumer advertising [111, 112] or social learning, which includes word-of-mouth and peer effects [113, 114].[9] More closely related to our study, a number of papers show that "report cards" revealing information about product quality can af-

[7] AIDS stands for Acquired Immune Deficiency Syndrome.

[8] To fix ideas, Appendix C.1 presents a theoretical model that formalizes the logic behind our interpretation of findings.

[9] The impact of social learning on demand has been shown in a variety of contexts, including the adoption of new crops [115, 116, 117] and job uptake [107]. See [118] for a comprehensive review. Other research has studied the effect of online reviews. [119] demonstrate how *Yelp* reviews affect restaurant choices, and [120] show that *eBay* reputation affects purchasing decisions.

fect choices when quality is uncertain.[10] In our study, we incorporate consumer-level data, which means we can study the impact of reviews not only on consumer choices, but also on subsequent outcomes. In this sense, our study is related to [130], who demonstrate that changes in restaurant choices in response to the posting of health inspection grades lowered incidence of hospital admissions related to food poisoning. Also related, [131] show that providing school test score information to lower-income families affects school choice, which in turn increases students' test scores. Similarly, we show that expert reviews affect consumer demand for medical treatment, which has subsequent impacts on their health outcomes.

An advantage of our study is that we incorporate information on objective product qualities along with reviews from multiple, possibly conflicting experts. This allows us to examine how reviews relate to objective product qualities along with heterogeneity in consumer responses to disagreements. We can thus provide novel evidence that the way in which experts weight product qualities in their reviews affects how consumers incorporate these reviews into their decisions. This point relates our study to an emerging literature on the demand for information. For example, [132] uses evidence from field experiments to show that individuals demand information, though they tend to underpay for it. [133] show that agent willingness-to-pay for information rises when the rewards from information are higher and [134] show that when making

[10] Information in the form of audits or report cards affects election winners [121], stock-buying [122], Medicare enrollment [123], health plan choice [124] and health care provider choice [125], hospital patient volumes [126], and investments in the housing market [127] and education [128]. [129] show that agents are willing to pay for information about charity recipients when agents' charitable giving is responsive to recipient type.

risky decisions, agents pay for information based on the likelihood of information being ex-post optimal. Relatedly, [135] show that when hospital report cards provide information that differ from patients' prior beliefs about hospital quality, patients switch to higher-quality hospitals.

By focusing on disagreements among experts in high-stakes contexts, we also relate to a literature demonstrating that reliance on low-cost information sources, such as expert reviews, can be problematic. For example, [136] show that information contained in health care "report cards" decreased patient and social welfare by inducing health care providers to decline treatment to sicker patients. [137] find that online hotel reviews that affect demand are subject to manipulation. Relatedly, in a study of expert judges of a musical competition, [138] show evidence that judges' rankings are often the result of random ordering of the performers and not the underlying performance quality. Yet, judges' rankings affect performers' subsequent careers.[11] The idea is that reviews, either from experts or other users, might not provide useful or accurate information, but could still affect economic decisions and outcomes. The disagreements between reviewers that we examine might suggest that at least one expert is "wrong," which could mean that reliance on reviews could harm patients. Our findings suggest a different interpretation. We argue that disagreements reflect that experts generate reviews that place different weights on multiple drug characteristics. Consumers therefore respond differently to divergent reviews, which suggests

[11] Relatedly, [139] show that a picture of a smiling woman on a loan brochure affects demand for the loan.

that they demand different information depending on their current health status and follow conflicting expert reviews accordingly.

Finally, we contribute to a literature examining health investments under uncertainty. For example, [140] show the effects of uncertainty and learning in the demand for anti-ulcer drugs.[12] [142] model how doctors update their beliefs about drug quality relative to existing drugs after observing the new drug's effects on their patients. Further studies examine how direct-to-consumer advertising [143], spillover effects from advertising of similar drugs [144], detailing [145, 146] and publicity [147] affect demand for pharmaceuticals when drug quality is uncertain.[13] There is also evidence of peer effects in healthcare adoption ([149]; [150]; [151]).[14] We show evidence of a novel way that consumers making health investments mitigate uncertainty: by incorporating expertise from potentially conflicting sources in a way that depends on their health objectives.

The rest of this paper is organized as follows. Section 3.2 discusses our data sources, sample construction and preliminary data analysis at the drug level. Section 3.3 constructs combination-level data (as HIV drugs are consumed in combination with one another), and presents a preliminary analysis at the drug-combination level.

[12] Related to learning, [141] designs a framework to analyze how price and promotion influence the learning process of the doctor and the patient and applies his model to depression care.

[13] Related, [148] study promotion spillovers in demand for HIV drugs.

[14] Theoretical work on social learning from peers can be traced back to [152] and [153], who show that informational cascades can explain herd behavior and fads. [154] presents a theoretical model of decision making with advice from outside sources (such as word-of-mouth advice and observational learning). [155, 156] write a behavioral game-theoretic model to explain limited strategic thinking at the movie box-office.

Section 3.4 describes our econometric model. Section 3.5 presents main results. Section 3.6 concludes.

3.2 Data: Drugs, Reviews and Demand

In this section, we introduce the data set used in our analysis. First, we introduce our two data sources. The first is a large panel data set on HIV+ men's treatment choices and health outcomes. The second contains expert drug reviews written in the magazine *Positively Aware*. Even though HIV drugs are consumed in bundles (an issue we address in Section 3.3), we conduct our preliminary analysis at the drug level to establish some basic patterns in the data. In particular, we look at how reviews published in *Positively Aware* relate to objective drug quality measures (also obtained from the magazine), the relationship between reviews and drug consumption, and how reviews evolve over a drug's lifecycle.

3.2.1 Data Sources

Data from the Multi-Center AIDS Cohort Study. We use the publicly available dataset from the Multi-Center AIDS Cohort Study (henceforth, MACS), an ongoing study of the natural and treated histories of HIV+ homosexual and bisexual men that was started in 1983.[15] The study is conducted in four cities: Baltimore, Chicago,

[15] The study also follows HIV-negative (henceforth, HIV−) men, but we exclude them from our analysis since over our sample period it is exceedingly rare that uninfected men consume HIV drugs.

Pittsburgh and Los Angeles.[16] At each semi-annual visit (conducted in March and September of each year), data are collected on medical treatment choices, health status and a host of socio-demographic measures, including employment, income and in education. The MACS data set consists of 6,843 individuals over 50 (semi-annual) visits. We restrict our attention to HIV+ individuals for the time period from 1997 to 2008, which is when drug reviews from the *Positively Aware* Drug Guides — our second data source — are available. Restricting our sample leaves us with an unbalanced panel of 1,330 individuals consisting of 13,472 observations, where each observation is an individual-visit dyad.

The MACS dataset not only provides us with individual-level drug choices but also includes two measures of health status relevant to individuals with HIV. The first is an objective measure of the individual's immune system health. At each interview, a blood test is conducted to measure the subject's CD4 count, which is defined as the number of white blood cells per mm^3 of blood. Typical CD4 counts range between 500 and 1000 for uninfected (HIV$-$) individuals and lower counts indicate that the immune system is compromised by HIV. Counts below 300 indicate the individual suffers from AIDS, a condition where the immune system has been compromised to

[16]Data in this manuscript were collected by the Multi-Center AIDS Cohort Study (MACS) with centers (Principal Investigators) at The Johns Hopkins Bloomberg School of Public Health (Joseph B. Margolick, Lisa P. Jacobson); Howard Brown Health Center, Feinberg School of Medicine, Northwestern University; Cook County Bureau of Health Services (John P. Phair, Steven M. Wolinsky), University of California, Los Angeles (Roger Detels); and University of Pittsburgh (Charles R. Rinaldo). The MACS is funded by the National Institute of Allergy and Infectious Diseases, with additional supplemental funding from the National Cancer Institute. UO1-AI-35042, 5-MO1-RR-00052 (GCRC), UO1-AI-35043, UO1-AI-35039, UO1-AI-35040, UO1-AI-35041. Website located at http://www.statepi.jhsph.edu/macs/macs.html.

such a degree that it loses functionality and cannot fight off common infections. The second health measure consists of subjects' own reports of their physical ailments, including nausea, headache, fever, diarrhea and drenching sweats. These physical ailments reflect side effects of medical treatments, but can also be symptoms of HIV infection if CD4 counts are low.

Data from *Positively Aware*. The second data source we use is a drug guide published annually since 1997 in an HIV lifestyle magazine known as *Positively Aware*, which contains drug reviews for all FDA-approved drugs and drugs nearing approval.[17] While the magazine is issued semi-monthly (six regular issues per year), the comprehensive drug guide is published annually joint with the January/February issue. The magazine's contributing writers and columnists are professionals in the field of HIV/AIDS, including HIV specialist physicians from the US, people living with HIV and advocates. The magazine is widely known in the HIV+ community and distributed for free. To get a sense of their outreach, in their media kit for 2010, the magazine publisher guarantees a minimum circulation of 100,000 copies, with 75,000 copies distributed to more than 1,900 community-based organizations and 700 Walgreens pharmacies across the US, 7,000 copies distributed at more than 200 venues, 5,000 copies distributed at HIV/AIDS conferences and events, 10,000 copies sent to individual subscribers, 1,500 copies to members of the American Academy of HIV

[17] *Positively Aware* is a not-for-profit HIV/AIDS treatment journal published by Test Positive Aware Network (TPAN).TPAN is a 501c3, not-for-profit AIDS Service Organization (ASO) based in Chicago, IL.

Medicine, and 1,500 copies to media, HIV advocates and pharmaceutical representatives.

The aim of the drug guides is to present information about HIV drugs in a form that is easy to decipher and comparable across drugs. It is meant as a guide for patients who are just starting therapy, as well as those who have been on treatment for a long time, helping patients discuss their treatment options with their doctors and decide whether or not an alternative treatment regimen might be more suitable. From 1997 until 2007, the magazines and the annual drug guides were only available in print. However, starting in 2007, the Drug Guides have also been available on the magazine's website, `positivelyaware.com`.

The drug guides offer rich information on HIV drug quality. Measures include the number of side effects observed in clinical trials, type(s) of side effects, severity of side effects, food restrictions for each drug, dosage frequency, drug interactions, and the drug's annual cost.[18] Most importantly for this study, the drug guides include reviews for each drug from both an HIV physician and a community activist (see Figure C.1 for a sample page from the 2008 drug guide for AZT). To our knowledge, *Positively Aware* provides the only source of expert reviews for all HIV drugs available on the market at a given point in time.[19]

[18] A list of all variables constructed using information from the magazines, along with their definitions, is presented in Appendix C.2.

[19] An online search of HIV drug guides returns a host of resources available for people who want information on HIV drugs. However, none of them publishes expert reviews on all FDA-approved HIV drugs on the market in our time period of analysis. The only source of user reviews for HIV drugs are `drugs.com` but they are only available after our period of analysis.

3.2.2 Coding Textual Expert Reviews

Typically, in the existing literature on the impact of expert or customer reviews on product demand, the 'expert' review variable is binary (Good or Bad) or categorical (for example, number of stars). As can be seen in Figure C.1, our expert reviews are not numerical ratings, but written text. The analysis of text is problematic and open to subjective interpretation. Thus, an important question for us is how to code reviews for subsequent analysis. One of the ways some authors have gotten around this problem is to use the length of the text as a proxy for whether the review is positive or negative, with longer text signifying a "mixed" review [157]. However, the reviews for most drugs in the *Positively Aware* drug guides are similar in length and gauging the quality of a review from its length would produce a very noisy measure of the doctors' and activists' valuation of the drug. For some drugs a negative review by the activist is long, as he or she narrates a personal experience, or the experiences of friends, while for other drugs a positive review by a doctor or activist may be long, including for example descriptions of specific experiences when a particular drug helped to save a patient's life. Another option would be to use text analysis software to automate the coding of the reviews. Unfortunately, text analysis software is imperfect and cannot accurately capture the true flavor of the review, especially when the text may be using euphemisms, analogies or subtle sarcasm to convey the message.

To circumvent these problems, we assign a ranking to the reviews manually by developing a numerical scale and by reading each review and assigning a number to it. We use an ordinal rating of 1, 2 or 3 to classify each drug. A rating of 1 signifies a *negative* review and a rating of 3 a *positive* review. A rating of 2 means we cannot assign a 1 or a 3, which thus means that a review is mixed.[20] In what follows, when we mention the doctor's or activist's review, we in fact refer to our numerical interpretation of them. We provide the details of the criteria we followed to construct these numerical variables in Appendix C.2. In the following preliminary analysis, we confirm that higher reviews tend to predict better objective qualities, which is to be expected if higher reviews are informative of the underlying qualities of the drugs. Recall that while expert reviews are at the drug level, HIV drugs are often consumed in bundles. The method we use to aggregate our numerical measures at the bundle-level is addressed in Section 3.3.

3.2.3 Summary Statistics at the Individual and Drug Levels

We report summary statistics for the variables at the individual level in our sample in Table C.1. The average age of individuals in the sample is 47, with 54% of the sample composed of white individuals. Close to 20% of the individuals have only a

[20]To verify that our results are not being driven by the particular way in which the reviews were coded, we also employed two undergraduate students at Johns Hopkins University to separately recode the magazine reviews. Results of the paper are robust to differences in coding, and the robustness checks are available upon request from the corresponding author.

high school degree, while 50% of the sample has completed college education, and 54% of people work full time. The average CD4 count of individuals in our sample is 536, with 54% of individuals reporting non-decreasing CD4 count from one visit to the next and 63% of the patients reporting no ailments such as fatigue, sweats, and headache. Relevant to our later analysis, 20% of patients have a CD4 count of less than 300, which indicates that they are living with AIDS.

Table C.2 provides summary statistics for drug characteristics from *Positively Aware*. In total, we have data on 27 different drugs produced by 9 unique manufacturing firms that were on the market at some point during the period between 1997 and 2008.[21] In 1997, there were only 9 drugs to choose from, while in the last period of analysis, patients could choose between 25 different drugs.[22] On average, drugs have 13 side effects reported in clinical trials and have molecular interactions with 14 other drugs. The average pill burden for a drug is roughly 2 tablets, taken twice a day.[23]

Descriptive statistics also show that the average rating given by doctors is higher than that given by activists (2.02 versus 1.89) and the difference is statistically significant at the 10% level. This suggests that, on average, activists are more critical. This result is reinforced when we compare the fraction of 1's, 2's and 3's given by the

[21] A detailed description of all the drugs, with information on when each drug entered (and exited) the market, is presented in Table C.16 of Appendix C.2.

[22] We have a total of 27 different drugs over the entire sample period because two drugs, Hivid and Preveon, were discontinued before 2008.

[23] The Department of Health and Human Services (DHHS) maintains a list of drugs with 'preferred regimen' status. On average, 7 out of the 27 drugs on the market were given the preferred status.

two sets of experts, as shown in Figure C.2. While an activist gives the lowest rating 36% of the time, the doctor rates a drug 1 only 26.7% of the time. On the other hand, a drug gets the highest rating by a doctor 27.2% of the time, while the activist rates a drug positively 24.7% of the time. Differences in reviews provide preliminary evidence that drug reviews could depend on differences in how experts weight different drug characteristics when generating a review. The last row of Table C.2 shows that the doctor and activist disagree (i.e., give a different rating for the same drug) 39% of the time.[24]

3.2.4 Drug Reviews, Drug Characteristics and Consumption

Though our main analysis focuses on the impact of reviews on the consumption of combinations of drugs, here we show key patterns emerging when we examine individual drug reviews and consumption. First, we show that higher expert reviews are associated with better objective drug qualities recorded in *Positively Aware*. Second, we show that higher reviews predict higher drug consumption. Third, we examine how reviews evolve over a drug's lifecycle, showing that reviews seem to decline over time and that the decline is partly explained by the introduction of new and better drugs into the market. The latter point is important since it will serve as the

[24]Note that having two sources of reviews for each drug helps identify separate effects on demand for reviews written by doctors and reviews written by activists.

motivation for our IV strategy, which is described in Section 3.4.

Reviews and Drug Characteristics. We first investigate how objective drug qualities as reported in the annual drug guide relate to expert reviews. Table C.3 presents results for the relationship between doctor and activist ratings and objective qualities in the magazine. As a first pass, in columns (1) and (2) we regress doctor's and activist's reviews, respectively, on drug characteristics by OLS. We find that, on average, better drugs receive better reviews, as expected. The higher the number of reported side effects and number of drug interactions of a drug, the lower both experts' ratings (though the effects are statistically insignificant). As dosage frequency increases, indicating difficulty in following the drug regimen and increasing the chance of missed doses, both expert ratings decrease. Given that reviews are categorical variables, in columns (3) and (4) we estimate the same relationships using an ordered probit model. We obtain qualitatively similar results.

Reviews and Consumption. To relate reviews to consumption at the drug level, we use individual-level data from MACS to construct drug-level *pseudo* market shares, defined as the fraction of people taking a particular drug out of the total number of HIV+ men in the sample.[25] Table C.4 presents the results of the linear regression of drug-level market shares on reviews. Columns (1) and (2) show that both the doctor's and activist's reviews are positively correlated with demand. Column (3)

[25]Note that these are not market shares since patients often take more than one drug at the same time. Hence, our *pseudo* market shares do not add to 1. These variables just measure the number of people that take a given drug normalized by the total number of potential consumers at any given point in time. We formally address consumption of bundles in Sections 3.3 and 3.4.

shows that when we control for both ratings together along with drug characteristics, both reviews still predict demand positively. Next, we show that average doctor reviews of other drugs in a combo predict lower demand. In Column (4), we add the average of reviews of all other drugs taken by the individual at the same time. While we continue to find that higher reviews by the doctor and the activist predict higher demand for the drug, higher doctor reviews for other drugs in the combination predict lower demand. In other words, when consumers combine drugs, for some drugs in their bundle, higher doctor reviews predict lower demand.[26] This finding suggests that, once we explicitly treat consumers as choosing bundles, we might expect a negative relationship between doctors' reviews and market shares, a point we revisit in Section 3.5.1 when we conduct our combo-level analysis.

Reviews over Drug Lifecycle. In our data, drugs are reviewed every year by two experts and reviews might differ not only across experts but also over time. Here, we look at how reviews for the same drug vary over the lifecycle of the drug. In general, there seems to be a downward trend in reviews from both experts over time, as illustrated in Figure C.3, which plots average reviews by drug age.[27] One possible reason for this "deflation" could be that reviews are relative to other available drugs in the market.[28] If so, as technology improves, reviewers may lower their reviews for

[26]On the other hand, higher activist reviews for other drugs in the combination predict higher demand for the drug.

[27]Age of the drug is measured as the number of years the drug has been on the market since introduction i.e. drug age = current year - year of introduction.

[28]Another possibility, explored further in Section 3.3.2, is that objective drug qualities decrease over time and reviews just reflect this decrease. When studying drugs at the combination level, we show some evidence of declining effectiveness, but reduced side effects as drugs in each treatment age.

older drugs. What once was regarded as a stellar drug may now be superseded by a newer, better drug. If this is the case, we would expect variation in how much reviews change for a given drug depending on the quality of rival drugs, conditional on a drug's own characteristics (which might also change over time). We test this hypothesis in Section 3.3.2, and we find that higher rival drug qualities lead to lower drug reviews. This finding motivates our identification strategy. The idea is to instrument for reviews using the qualities of the set of rivals at any point in time, where the set of rivals shifts over time due to the emergence of new drugs. A more detailed discussion of our identification strategy is presented in Section 3.4.2.

3.3 Combination-Level Data: Preliminary Analysis

Section 2 presented some basic patterns in the data linking individual drug reviews to objective drug qualities and drug consumption patterns. However, HIV drugs are rarely consumed individually and are instead consumed in bundles. Bundles of HIV drugs are sometimes called *cocktails*, *combination therapy*, *combos* or simply *treatments*. At a given point in time, a large majority of HIV patients combine two drugs or more in order to build a regimen that is effective in fighting HIV. Figure C.4

These patterns are consistent with drugs losing effectiveness as the virus mutates and with patients gaining tolerance to side effects as doctors and patients gain experience with it. In subsequent analyses, we control for time-varying objective drug qualities to capture changes in quality over time.

shows the distribution of drugs in the combinations. Conditional on taking at least one drug, around 35% of HIV+ individuals take 3 drugs at the same time, while 25% are following monotherapy, i.e., only taking one drug at the time of a visit.

A challenge for our subsequent analysis is that each drug is reviewed individually. In this section, we describe how we construct a data set for analysis of demand for combinations, which requires that we aggregate expert reviews for individual drugs into combination-level reviews. Then, we conduct a preliminary data analysis relating expert reviews to the demand for HIV drug combinations. We end this section with a brief discussion of alternative interpretations of the observed relationships between drug reviews and drug demand.

3.3.1 Combination Data Variable Construction

For our combination-level analysis, we construct the choice set, reviews for combos, combo-level objective qualities and combo-level market shares.

Constructing the Choice Set. To study bundling, we return to the individual-level data from MACS and construct a dataset of combination choices. We restrict our attention to individuals who are taking 5 or fewer drugs during one visit.[29] This leaves us with a total of 1,248 unique drug combinations. A large number of these combinations, however, are taken by a small number of individuals and can be thought

[29] Patients who are taking more than 5 drugs simultaneously are also those who are extremely sick and are probably taking multiple drugs to find one that can decrease their viral load. Since this is not how patients, on average, make medication choices, we exclude these people from our sample. By doing so, we lose less than 2% of observations.

of as experimental combos. Therefore, in order to reduce the choice set so that it is manageable from a computational perspective, as well as to be able to construct objective quality measures for every combination in our choice set, we define a 'fringe' category, in which we bunch together all combinations that are taken by fewer than 25 people.[30] That leaves us with 79 unique combinations in total across all years in our sample plus the 'fringe' category and the outside option of taking no HIV drug. Note, however, that the choice set is evolving over time. The number of combos over time (excluding the outside option) is illustrated in Figure C.5.[31] We see that patients have a minimum of 21 drug combinations to choose from for the first year of our sample (early 1997), and a maximum of 58 drug combinations in late 2004.

Constructing Reviews for Drug Combinations. The doctor and activist reviews are only available for each drug, not all possible drug combinations. Therefore, in order to construct expert reviews for different drug combinations, we average over the reviews of each drug component of the combination.[32] Table C.5 presents summary statistics for the combo level variables. Panel (A) shows that the average doctor's rating for a combination is 2.18, while the average activist's reviews is 2.07.[33] Consistent with our previous results, doctor's reviews are significantly higher. Using the

[30]A combination can belong to the fringe category in some visits, but not others.

[31]Over the span of 10 years, different drug combinations fall in and out of favor, especially when new drugs are introduced on the market. The total number of unique alternatives we observe is 81, but not all of these alternatives are encountered in any given time period.

[32]For example, if AZT has a rating of 2 and 3TC has a rating of 1, then the combination AZT-3TC will have a rating of 1.5

[33]In [148], who also study HIV drugs, promotions are studied at the individual drug level even though drugs are prescribed in combinations with others.

average of the individual drug reviews as our measure of combo-level reviews may overlook factors that consumers consider, such the minimum or maximum review or the variance. To explore these possibilities, after we present our main results, we assess robustness to alternative ways of aggregating individual drug reviews for combinations. Main findings are robust to these alternatives.

Objective Qualities: Effectiveness and Side Effects. A key advantage of the MACS data set is that it allows us to construct objective drug combination quality measures that are crucial for our demand estimation. In particular, we follow [110] and construct two objective quality measures for each treatment at each point in time.[34] The first measure aims to quantify treatment effectiveness at improving underlying health (as measured by CD4 count levels). The second provides a measure of the treatment side effects. We allow these measures to change each period over the lifecycle of a treatment to capture possible differences over time in treatment quality that arise, for example, if HIV mutates.[35]

The way we construct these objective quality measures for the different combinations is as follows. For each combination c, we run a probit regression on demographic characteristics to predict c's probability of non-decreasing CD4 count and probabil-

[34] From now on we use the terms "treatment" and "combination" interchangeably even though some consumers are observed taking a single drug.

[35] When we allow these quality measures to vary over time, we find that drug efficacy tends to decline and drug side effects become less frequent. The latter may occur if individuals or doctors get used to using or dosing medications over time. Alternative specifications we have tried include pooling observations to generate a single measure over time for a drug and rolling averages, which generate smoother changes over time. Our results are robust to the use of constant quality measures over time or rolling averages and the results of this robustness check are available upon request from the corresponding author.

ity of no ailment on the sample of individuals taking c. To obtain treatment-level objective quality measures, we average over all individuals taking c. We allow the quality measures to be time-variant by letting the probit coefficients vary over time. Formally, to construct combo c's measure of effectiveness, we first fit a probit model of the likelihood that a patient will experience an increase in his CD4 count in period $t+1$ when taking combo c at time t, conditional on patient's characteristics. Letting $\mathrm{CD4}_{nt}$ be individual n's CD4 count at time t, we estimate the model

$$\Pr_{ct}(\mathrm{CD4}_{nt+1} \geq \mathrm{CD4}_{nt}|X_{nt}) = \Phi\left(X'_{nt}\beta_{ct}^{\mathrm{CD4}}\right) \tag{3.1}$$

on the sample of individuals who take combo c at time t, where X_{nt} is a vector of demographic controls including patient n's age, race, education level and work status as well as n's CD4 count at t, and $\Phi(\cdot)$ is the standard normal cdf. We fit the probit for each combo separately (so that all coefficients can vary for each combo), and obtain the predicted probability of non-decreasing CD4 count for each individual in each visit. In order to get the combo-level predicted probabilities, we average the predicted probabilities over all n that take combo c at time t. The aim with this procedure is to compute an average treatment effect, which consumers use when choosing a treatment.

Similarly, our measure of combo c's side effects is calculated as the average likelihood that combo c produces no ailments.[36] Let noail_{nt} be a dummy variable that

[36]We define an individual as being free of ailments if he reports no nausea, headache, fever,

takes the value 1 if patient n experiences no ailments at time t and 0 otherwise. We fit the model

$$\Pr_{ct}(\text{noail}_{nt} = 1 | X_{nt}) = \Phi(X'_{nt}\beta^{\text{noail}}_{ct}), \tag{3.2}$$

on the sample of individuals who take combo c at time t and where X_{nt} is the same vector of covariates as above and $\Phi(\cdot)$ is the standard normal cdf. As before, we fit a probit model for each combo and obtain the predicted probability of no ailment for each individual in each visit. In order to get the drug-level predicted probabilities, we then average the predicted probabilities over all n that take combo c at time t.[37] Table C.5, panel (B) presents the summary statistics for the constructed objective quality measures. The probability of non-decreasing CD4 count for the average drug combination is 55%, while the probability of no ailment in the period after taking the combination is 60%.[38]

Constructing treatment quality measures using individual-level data stands in contrast to other demand estimation contexts, where product characteristics (e.g., car size or horsepower) are directly observed in the data. Controlling for consumer-level characteristics when constructing these measures helps to eliminate potential

diarrhea, or drenching sweats in a period.

[37] An alternative approach would use probit coefficients to predict treatment effects for each set of consumer characteristics. We do not follow this approach since the aim is to capture that consumers likely know how drugs work in general, but not necessarily how they work for each set of characteristics, many of which are not observable. However, we note that reduced-form estimates remain unchanged if we allow for consumer-specific treatment effects.

[38] Since the 'fringe' category is composed of different combinations within and across different time periods, each of which have their own objective quality value, we average over different combos within the same time period t to obtain one value per time period for the objective quality measures for 'fringe'.

selection bias. Most importantly, we control for individual health, which could drive treatment choices along with one-period-ahead health or side effects, and could thus lead to bias in estimated coefficients if omitted.[39] We return to the discussion of the consequences of using constructed treatment characteristics in Section 3.4.2, when we discuss our identification strategy

Combination Market Shares. As mentioned before, the data in the MACS dataset are collected twice a year. Thus, we can construct market shares for two six-month periods (one for April–September and the other for October–March) in each year. Let C_{nct} be a dummy variable that takes value 1 if patient n responded as having taken combination c at visit t and 0 otherwise. Then, the market share for combination c at time period t is given by:

$$s_{ct} = \frac{\sum_{n=1}^{N_t} C_{nct}}{N_t}, \tag{3.3}$$

where N_t is the total number of HIV+ individuals at visit t.

Table C.5, panel (C) provides some summary statistics of combo-level market shares.The average market share of the outside option (taking no drug) is 19%, while the market share of the 'Fringe' group is, on average, 32%. The average market share for combos other than 'fringe' and the outside option is 1%, with a maximum market share of 18%. Figure C.6 shows how the market share of the outside option

[39] In additional results, we also control for consumer-level fixed effects in constructing treatment quality measures and find that main results do not change.

evolves over the time frame of our analysis. The market share for the outside option picks up in October 1999, reaching a peak in April 2003, going down for the next few visits, and then finally reaching a maximum in October 2007. In April 2008, the market share of the outside option fall drastically, from 27% to around 15%. This is because in April 2008, the drug Atripla was introduced on the market, which had a market share of 19% at the time of introduction, suggesting that a large proportion of patients who were off drugs switched to Atripla after its introduction.[40]

3.3.2 Preliminary Combination-Level Analysis

Having constructed combo-level reviews, objective quality measures and market shares, we now establish reduced-form results from our data. First, we study objective qualities and demand to see if individuals prefer better quality drugs. Second, we explore the relationship between combo-level reviews and objective qualities. Third, we relate reviews and demand before and after we control for objective qualities to see if reviews have predictive power even after we control for observable drug quality levels.[41]

Table C.6 shows how objective qualities from the MACS dataset and from the *Positively Aware* drug guide relate to combo demand.[42] Columns (1) through (3)

[40] Other significant changes in the share of the outside option can also be linked to years when new drugs were introduced on the market.

[41] We also construct objective qualities from MACS at the drug level and relate reviews and drug consumption before and after controlling for these objective qualities, and find similar patterns. However, since that is not how drugs are actually consumed, we do not report these results as part of our reduced form analysis, though the results are available upon request from the authors.

[42] We construct combo-level qualities using the *Positively Aware* data by averaging across all drugs

show that if the probability of no ailment of a combo increases (i.e., the side effects from taking that combo go down), the demand for that combo increases. Similarly, if the probability of non-decreasing CD4 count increases with use of a specific combo, then its demand is also larger. In particular, a one unit increase in the probability of no ailment increases demand by 2.1%, while a unit increase in the probability of non-decreasing CD4 count increases demand by 1.7%.[43] In columns (4) through (6) we also control for the objective qualities included in the annual guides. As expected, as the number of reported side effects for a combo increases, or if the pill burden or number of food restrictions for a combo increases, the demand for that combo goes down. Lastly, if dosage frequency for a combo increases (which increases the likelihood of missed doses and not being able to follow the drug regimen strictly), demand for that combo decreases. Therefore, all these results show that people, on average, prefer better quality drugs.

In Table C.7, we show how objective qualities from MACS relate to expert reviews. We find that both the doctor and the activist give a higher rating to combos that have a high probability of no ailment and probability of non-decreasing CD4 count. Therefore, consistent with drug-level results using objective qualities from *Positively Aware*, we find that doctor and activist reviews are higher for combos that are more effective and have lower side effects.

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in a combo. To calculate the combo-level pill burden, however, we sum the total number of pills taken for each drug in a combination.

[43]The average marginal effect is calculated by first calculating the marginal effect for each combo-year dyad and then averaging across the entire sample.

Moving on to how market shares are related to reviews and drug qualities, Table C.8 presents results from regressions of market shares on reviews and objective qualities at the combo level. In columns (1) and (2), we see that a doctor's review positively predicts combo demand, even when we control for objective quality measures. Columns (3) and (4) show that an activist's review also positively predicts combo demand, even after controlling for objective quality measures. However, in columns (5) and (6), when we include both experts' reviews together, we see a reversal of sign for the doctor: that is, the doctor's review now negatively predicts combo demand (though the coefficient is not significant when we control for MACS objective qualities). On the other hand, a higher activist's review positively predicts combo-level market share, even after we control for the probability of no ailment and probability of non-decreasing CD4 count.

Lastly, in Figure C.7, we plot the combo ratings and combo objective qualities over combos' lifecycle. Panel (a) shows how doctors' and activists' reviews evolve as the combo ages. As in the previous reduced form analysis, we find that combo reviews are decreasing as the drug combination ages. Panel (b) shows how the probability of no ailment and probability of non-decreasing CD4 count of combos changes over the combination lifecycle. As the drug ages, probability of no ailment increases, indicating that side effects decrease as the combination becomes older, while the probability of non-decreasing CD4 count decreases for older combinations, suggesting that old combinations are not as effective as new ones. In panel (c), we plot residual ratings after controlling for objective quality measures of the combo, and find that even when we control for the evolution of a combination's quality, reviews are still decreasing over time. We use this fact to motivate our identification strategy in Section 3.4.2.

3.3.3 Expert Reviews and Demand: Alternative Explanations

The previous analysis provides preliminary evidence that expert reviews published in *Positively Aware* predict market shares for HIV drugs. However, there are several alternative explanations which would also explain the correlation between combo reviews and combo demand that we find in the data. One possibility is that reviews do not drive demand but simply reflect a drug's observed qualities which in turn is the demand driver. However, in the previous section, we showed that reviews continue to predict market shares even after we control for objective quality measures. Still, it is possible that reviews are not exogenous. One concern is simultaneity. It may be the case the reviews simply reflect demand patterns. Another possibility is unobserved drug heterogeneity. Magazine reviews may reflect drug qualities that are not observable to the econometrician but are observable to patients and doctors who make treatment decisions and therefore affect demand. We defer the formal treatment of the endogeneity issue to Section 3.4.

A second possibility is that the impact of reviews on demand for HIV drugs is indeed causal, but that it is not due to patients reading *Positively Aware*. For example, *Positively Aware* magazines are not the only source of information about drugs available to patients. Other magazines could provide similar information and affect demand. However, to our knowledge, *Positively Aware* drug guides are the only source of information in which patients can read reviews about all FDA approved drugs from a doctor and HIV activist in a systematic way.

The third potential story is related to the previous one. It could be that the true demand driver is collective, evolving knowledge about drug quality and the reviews are just reflecting it. We provide some suggestive evidence that this is not the case. We do so by exploiting the timing of the reviews relative to when we observe drug choices. In particular, given that the annual guide is published in January/February and data on drug choices are collected both in April and October, we consider three distinct market share windows for our analysis. Relative to reviews published in Jan/Feb of year t, we can construct market shares realized *before* the magazine is published (i.e., market shares for the window April-September in period $t-1$), market shares for the window that overlaps with the period *during* which magazine is published (i.e., market shares for the window October-March in period $t-1$), and market shares realized *after* the magazine has been published (i.e., market share for the windows April-September and October-March in period t). The timeline of events is illustrated in Figure C.8.

If the reviews solely capture evolving social knowledge about drugs, by construction they would only capture knowledge from the 12 months prior to publishing. Thus, we could falsify the social knowledge hypothesis if reviews at period t have no effect on market shares for the *before* and *during* windows at $t-1$, after controlling for reviews at $t-1$. Running these two regressions we find that reviews at t have no significant effect.[44] Moreover, when we run the regressions of market shares for the *after* window at t and $t+1$ we find that reviews published in period t do have a significant effect. We interpret this as suggestive evidence that reviews from *Positively Aware* (rather than evolving social knowledge) drive demand for HIV drugs.

3.4 Econometric Model and Identification

In this section, we specify an econometric model of demand for HIV combos. The purpose is twofold. First, the estimates of the coefficients of the structural model will allow us to obtain own- and cross-review elasticities. Estimates of these elasticities are crucial to quantify the effect of reviews on health outcomes. Second, the model makes explicit the identification issue we need to overcome and will help in understanding the logic behind our identification argument.

[44]Results available upon request.

3.4.1 Model Specification

We study combination choice using a discrete choice demand model at the combo level. Let $\mathcal{J}_t$ denote the choice set at time period t. To explain choices, we allow the utility of an individual i, $i = 1, \ldots, n$, from consuming combination $j \in \mathcal{J}_t$ at time t to depend on the drug characteristics — both observed and unobserved — as well as his demographic characteristics, health status, and unobserved taste shocks.[45] Let x_{jt} be a K-dimensional vector of observed product characteristics — including the doctor's and activist's reviews — at time t and let ξ_{jt} denote the unobserved product characteristic.[46] Also, let z_{it} be an R-dimensional vector of individual i's characteristics at time t, including age, education (dummies for whether the individual is a high school or college graduate), work status (dummy for full-time work), race (dummy for black), AIDS status, and whether or not the individual was taking the same combination in the last period. We can then write the utility i gets from consuming alternative j at time t as

$$u_{ijt} = \sum_k x_{jtk}\tilde{\beta}_{ik} + \xi_{jt} + \epsilon_{ijt}, \tag{3.4}$$

[45] The model we specify here is used to estimate the impact of reviews on demand. Following literature on advertising, which uses a similar framework, our model treats reviews as an additional product characteristic that drives demand by affecting the utility of a given product. Alternatively, a fully specified structural demand model could treat individuals as not having preferences over reviews, but as relying on reviews for additional information about drug characteristics over which they do have preferences, but do not fully observe. If so, in our current setup, we are recovering a reduced-form relationship between reviews and demand. This limits the types of counterfactuals we can perform, a point we return to in Section 3.5.3.

[46] Note that we treat each combination j at time t as a separate product, so that AZT–3TC in 1997 is a different product that AZT–3TC in 1998.

with

$$\tilde{\beta}_{ik} = \bar{\beta}_k + \sum_r z_{irt}\beta_{kr}, \tag{3.5}$$

where $\tilde{\beta}_{ik}$ is individual $i's$ taste for product characteristic k, which depends on his observed individual-level characteristics z_i, and ϵ_{ijt} represents a shock to preferences which we assume is distributed Type-I extreme value and independent across choices and individuals. Letting

$$\delta_{jt} = \sum_k x_{jtk}\bar{\beta}_k + \xi_{jt} \tag{3.6}$$

denote the mean utility level we can rewrite the utility as

$$u_{ijt} = \delta_{jt} + \sum_{k,r} x_{jtk} z_{ir}\beta_{kr} + \epsilon_{ijt}. \tag{3.7}$$

Market-level aggregate consumer behavior is obtained by aggregating the choices implied by the individual utility maximization over the population distribution of individual characteristics. Let $\mathcal{P}(\mathbf{w})$ denote the distribution of $\mathbf{w}$ in the population, where $\mathbf{w} = (\mathbf{z}, \boldsymbol{\epsilon})$ is the vector of observed and unobserved individual characteristics. Then, conditional on product characteristics, the fraction of individuals who choose combination j at time t is given by integrating over the set of individual characteristics that imply a preference for combo j at time t:

$$s_{jt}(\boldsymbol{\delta}, \boldsymbol{\beta}; \mathbf{x}, \mathcal{P}(\mathbf{w})) = \int_{A_{jt}(\boldsymbol{\delta}, \boldsymbol{\beta}; \mathbf{x})} \mathcal{P}(\mathbf{w}) d\mathbf{w}. \tag{3.8}$$

where

$$A_{jt}(\boldsymbol{\delta}, \boldsymbol{\beta}; \mathbf{x}) = \{\mathbf{w} : \max_{p \in \emptyset \cup \mathcal{J}_t}[u_{ipt}(\mathbf{w}; \boldsymbol{\delta}, \boldsymbol{\beta}, \mathbf{x})] = u_{ijt}\}. \tag{3.9}$$

Details about the estimation of the demand model are presented in Appendix C.3.

3.4.2 Identification

We know from Section 3.3.2 that doctors' and activists' reviews reflect observed combo characteristics. An endogeneity problem might arise if reviews also reflect unobserved combo quality. This problem is analogous to the price endogeneity issue that arises in traditional demand estimation (see, e.g., BLP). In order to establish a causal relationship between reviews and market share, we leverage the idea that the choice set is evolving over time, with new drugs entering the market every period. If combo entry is exogenous and reviews are *relative*, then the entry of new combos provides exogenous variation in reviews over the combo's lifecycle. Specifically, we use the average of (observable) qualities of rival combos on the market as an instrument for reviews. The intuition is that the quality of rival drugs should change the reviewer's relative valuation of an incumbent drug's quality, and will hence affect the review for that drug. Table C.9 shows how the doctor's and activist's reviews of a combo relate to the average quality of rival combos on the market. As expected, results show that (i) an increase in the objective qualities of a combo is positively correlated with its reviews; and, more importantly, (ii) an improvement in the average probability of no ailment or the average probability of non-decreasing CD4 count of rival combinations leads to a decrease in the reviews for the combination. A joint test of the rivals' objective quality measures show that both the average probability of non-decreasing CD4 count of rival combinations and the average probability of no ailment of rival combinations significantly affect doctors' and activists' ratings for a combination.

Our key identifying assumption is that rival treatments enter the market exogenously (technically, that the observable characteristics are orthogonal to the unobserved characteristics, $\boldsymbol{X} \perp \boldsymbol{\xi}$) and affect reviews by experts but are uncorrelated with incumbent treatment unobserved characteristics.[47] Note that the logic behind our instruments is similar in spirit to the one in BLP. In BLP, prices are endogenous and need to be instrumented. Prices are set in equilibrium by oligopolistic firms, and therefore prices not only depend on a given product's characteristics but also on the characteristics of its rivals. Therefore, rivals' characteristics are valid instruments under the assumption that product characteristics — other than price — are exogenous. In contrast to the instruments in BLP, we construct the treatment characteristics, and hence the instruments, from our patient-level data as described in Section 3.3.1. To the extent that there is selection into treatments based on patients' characteristics, this could undermine the validity of our instruments. To mitigate the effects of selection, we control for patient demographics and health in (3.1) and (3.2)

[47] It would be a threat to identification if the observed objective characteristics of rival treatments were correlated with the experts' reviews as well as with the unobserved characteristics of incumbent combinations.

and in our specification of the utility function.[48]

3.5 Findings

This section presents our main findings. We begin with estimates from our baseline model. Results are qualitatively similar to the reduced-form estimates we obtained previously. Higher activist reviews increase demand, whereas higher doctor reviews lower demand, even after controlling for objective treatment characteristics. To investigate this point further, we distinguish between cases where doctors and activists agree versus disagree. We show that higher reviews increase demand when doctors and activists agree. However, when they disagree, healthier consumers tend to follow the activist's review, while less healthy patients follow the doctor. The remainder of this section provides evidence that these patterns reflect how consumers trade off their demand for long run health and their distaste for treatment side effects.

[48]To fix ideas, if a negative change in a given drug's ξ induces patients to switch to other drugs in a random way, this poses no problem to us. The problem arises when switchers are, for example, systematically sicker. This could affect the drug characteristics we construct in a way that would potentially render them (positively) correlated with ξ. Controlling for individual health helps to mitigate this problem. It is worth noting that if sicker patients switch to other drugs, which lowers the quality of other drugs we estimate, this would induce a positive correlation between instruments and unobserved drug quality, which would bias estimates upward. As instruments negatively affect demand (through a negative impact on reviews), upward bias means our estimates are biased towards zero, suggesting that we estimate a lower bound on the true causal positive impact of reviews on demand.

3.5.1 Estimates of the Baseline Model and Robustness

We begin by estimating the parameters of the demand model given by equations (3.4) and (3.5), treating reviews from both experts as additional treatment characteristics, instrumenting for both using the average of the rivals' objective qualities. Table C.10 reports the logit coefficients. Column (1) shows that a higher doctor's review on its own raises demand. A one-unit increase in the doctor's review increases the likelihood the treatment is chosen by 1.5%.[49] This result also holds when we control for objective treatment qualities (see column (2)). Similarly, columns (3) and (4) show that a higher activist's review for a combination increases consumption. A one-unit increase in the activist's review for a combination increases demand by 2.2%.

When we include both reviews together, we find that a positive review from the doctor lowers demand, while a positive review from an activist raises demand (see columns (5) and (6)). This finding is in line with our previous reduced-form estimates. Keeping objective qualities and the activist's review fixed, an increase in the doctor's rating of one unit leads to a 2.9% decrease in demand, while an increase in activist's rating, keeping the doctor's review fixed, raises demand by 4.3% .[50]

[49]The percentage change in the probability of choosing a combo alternative is calculated for each combo-year dyad and then averaged across the entire sample.

[50]Note that in our IV logit specifications, once we control and instrument for activist's reviews, the coefficient on probability of non-decreasing CD4 count is negative. This negative coefficient captures how patients with different attributes (for example, those who are working full-time) may prefer combinations with fewer side effects but lower efficacy. In fact, in our demand model with individual attributes, we show that once we explicitly account for differences in patients' attributes such as race, work status etc., both objective qualities affect utility positively.

Next, we assess whether our results are robust to different ways of constructing combo-level reviews. First, we generate reviews for combos by calculating the percentage of drugs that have a rating of 3 in the combination. This relaxes the implicit cardinality assumption arising from our use of averages. Demand estimates using this definition of reviews are given in panel (A) of Table C.11. Notice that results are similar to our original specification. As before, we find that doctor's and activist's reviews positively predict demand when including them one at a time; however, when we control for both at the same time, we find that a higher doctor's review lowers demand. In panel (B) of Table C.11, we include a variable that controls for the percentage of drugs in a combo that have a rating of 2. Results do not change appreciably, though the negative effect of the doctor's review becomes insignificant.

Our second alternative specification includes the average review across all drugs in a combination as well as the standard deviation of reviews within each combination. The aim is to capture how patients value both the mean and the variance of individual product attributes (drug-level reviews) in the bundles they consume ([158], [159]).[51] Results using this specification are shown in panel (C) of Table C.11. For the doctor's review, after controlling for the average review, an increase in the standard deviation is negatively related to demand, though the relationship is not statistically significant. For the activist's review, the standard deviation of the reviews has a positive but

[51] [158] and [159] describe individual choices among an assortment of multi-attributed items in which the assortment could be made from a subset of all items available to individuals. In their mode, they allow a mean level of attribute for the assortment as well as the dispersion of attributes to affect utility.

insignificant relationship to demand once we control for objective qualities of the combination. In columns (5) and (6), we again see the reversal in sign for the average doctor's review when we include both the activist and doctor's review. Since we find no evidence that the standard deviation of reviews affects demand significantly once we control for the average reviews, we omit the standard deviations.[52]

3.5.2 Disagreements and Demand

At face value, it seems puzzling that demand responds negatively to higher doctor's reviews. To explore this result, we consider how consumers respond to reviews when the doctor and activist agree versus when they disagree. In fact, disagreements occur quite frequently: for roughly 60% of combination-time dyads.

To understand disagreements better, we first assess how they evolve over the age of the combination. For this exercise, we define a dummy variable, which takes a value of one if the activist's review is not equal to the doctor's review. Panel (a) of Figure C.9 depicts disagreements over drug age. Not surprisingly, most of the disagreements between the two experts occur when the combination is 'new', i.e., the combination has only been on the market and consumed by patients for three years or less. The experts disagree 75% of the time when the combination is new, but over time, specifically, when the combination has been part of the choice set for more than 6 years, the frequency of disagreements between the two experts declines.[53] We

[52] Additional robustness checks are presented in Appendix C.4.

[53] An exception is a high proportion of disagreements occurring when combo age is 11. This is

also consider the magnitude and direction of the disagreements. Panel (b) of Figure C.9 shows the distribution of the difference between the activist and doctor's review. When the two experts disagree, we are more likely to see a higher average review for the combination from the doctor than the activist.

Next, we explore the effect of disagreements on demand by interacting the doctor's and activist's review with a dummy for disagreements, and interacting the doctor's review with a dummy for agreements.[54] The coefficient on the interaction between agreements and the doctor's review captures the relationship between reviews and demand when the experts agree, while the coefficients on the interactions between disagreement and the two expert reviews capture which expert patients follow when experts disagree. The estimates are shown in Table C.12 (for comparison, column (1) reproduces the last column of Table C.10). In column (2), we see that, on average, if both experts agree and the combination gets a higher review, then demand rises. This finding means that patient demand rises when both the activist and the doctor ratings for a treatment are high. On average, a one unit increase in experts' rating when both experts agree leads to an increase in the probability of taking a combination by 1.8%. [55] To put this in context, to achieve the same increase in demand, the probability

driven by a set of combinations of old drugs (d4T, 3TC and Nevirapine). Removing these combinations does not affect our results.

[54]Note that when the experts agree, the activist's and doctor's reviews take the same value, so interacting the dummy for agreement with the activist review is redundant.

[55]We calculate the average marginal effect by first calculating the marginal effect for each combo-visit dyad, and then averaging across all combo-year dyads. Similarly, the percentage change in the probability of choosing a combo alternative is calculated for each combo-year dyad and then averaged across the entire sample.

of non-decreasing CD4 count would have to increase by 1.06 percentage points and the probability of not experiencing side effects when taking the treatment would have to increase by 0.85 percentage points.[56] According to Table C.5, on average across treatments, these measures of quality are 55% and 60%, respectively. Thus, a rise in reviews from neutral to positive has the same positive impact on demand as a 1.93% increase in our measure of effectiveness or a 1.43% increase in the probability of not causing ailments.[57]

When the experts disagree, however, a higher activist's review for a combination increases demand, while a higher doctor's review lowers demand. This result suggests that that the negative coefficient on the doctor's review from our baseline model is driven by cases when the doctor's review is at odds with the activist's. To explore this point a bit further, we also assess potential asymmetries in how patients respond to conflicting expert reviews. We calculate the difference between the activist's and doctor's review for each drug, generate a dummy for whether this difference is positive (the activist gives a higher review compared to the doctor) or negative (the activist's review is lower than the doctor's) and interact these dummies with the two experts' reviews. Results are shown in column (3) of Table C.12. Estimates show that when reviewers disagree, there is a significant effect on demand when the activist's review is lower than the doctor's. In particular, an increase in the doctor's (activist's) review

[56] These figures are calculated by using the marginal effects for the two objective qualities reported in Section 3.3.2.

[57] This comparison is similar to one made in [139], who show how much non-standard content (advertising) is worth versus standard determinants of demand — in their case, interest rates for loans.

has a negative (positive) effect on demand when the reviews differ and the activist's review is lower than the doctor's review. When the activist's review is higher that the doctor's, the effect of both reviews is not significant. This result provides further nuance to baseline estimates. The negative reaction to the doctor's review arises when doctors and activists disagree and, moreover, when the activists downgrades a drug that the doctor does not.

3.5.3 Conflicting Reviews, Side Effects and Demand for Expertise

Having established the importance of disagreements in explaining how patients respond to expert reviews, we now turn to understanding patient responses. We present three sets of empirical results, all of which rely on rich data on objective treatment qualities and individual characteristics. First, disagreements arise when treatments are effective, but have strong side effects, in which case they receive lower reviews from the activist, but not from the doctor. Second, following the activist's review over the doctor's leads to worse health, but reduced side effects. These results suggest the possibility that patients follow the activist in an effort to avoid treatments with harsh side effects. If so, we might expect sicker patients, who are willing to suffer side effects if drugs are effective, to follow the doctor. Our third empirical finding is to show that this is the case.

3.5.3.1 Disagreements and Objective Qualities

We begin by exploring the relationship between experts' ratings and objective qualities of treatments (probability of no ailment and probability of non-decreasing CD4 count) in the choice set to see if there are differences in how experts respond to these qualities when they disagree. In Table C.13, we regress doctors' and activists' ratings on the objective qualities of own and rival combos for the sample of combos for which the two experts disagree. We find that when the two experts disagree, the doctor's review increases if the probability of non-decreasing CD4 count of a combo increases, while the probability of no ailment has a statistically insignificant effect on doctor's rating. On the other hand, the activist responds positively to both objective quality measures.

We also consider the correlation between our two objective qualities grouped by the age of the combination in Table C.14. When experts agree, on average, the correlation between the two objective qualities is positive, implying that combos are either good or bad in both dimensions when there is an agreement.[58] On the other hand, when there are disagreements between the two experts, the correlation between objective qualities is negative. The last two columns of Table C.14 show that when there is a positive difference in the reviews (the activist gives a higher review than the doctor), on average, there is a strong negative correlation between the two

[58]For combination age between 4 and 7 years, the correlation between the objective qualities when the experts agree is negative. However, we find that the negative correlation is driven by combos containing two drugs: Zerit and Kaletra. Once we exclude those combos when calculating the correlations, we get a positive, though insignificant correlation between the two objective qualities

objective qualities, implying that for these combos, the trade-off between effectiveness and side effects is important. For cases in which we observe negative differences (the doctor gives a higher review than the activist), the correlation between the two quality measures is negative but small, except for when combo age is between 4 and 7 years.[59]

3.5.3.2 Expert Reviews and Health Outcomes

Next, we examine how reviews affect individuals' health outcomes (through their effect on combo choices). The way we quantify these effects is the following. We simulate how drug choices would have changed in the absence of the reviews. We consider three cases: (i) absence of activist reviews; (ii) absence of doctor reviews; and (iii) absence of both types of reviews. We then construct measures of individual-level health outcomes based on the counterfactual combo choices. We also simulate factual health outcomes including both reviews, and compare the counterfactual health outcomes to the simulated factual ones.[60] We focus on two key health outcomes: (i) the probability of having AIDS in the next period and (ii) the probability of having no ailment in the next period, both conditional on the individual's current period health status.

Our simulation results show that some people might get sicker by defying the doctor. However, they suffer fewer side effects. Figure C.10 shows the percent change

[59] The positive correlation in the age bracket between 4 and 7 is again being driven by drugs Zerit and Kaletra. When we exclude these two drugs from our analysis, we get a negative correlation when there is a negative difference.

[60] The simulations are performed by taking a random sample of 10,000 patients with replacement in each visit.

in the probability of having AIDS and having no ailments over the entire period of analysis compared to the baseline case in which the two reviews are present.[61] The dotted vertical lines on the figures indicate the introduction of at least two new drugs in the months spanning that visit (see Appendix C.5 for details on how the state of the market evolves over our analysis time period). Panel (a) shows the change in the probability of AIDS over time for the full sample. When we shut down both reviews, there is a modest decrease in the probability of AIDS. When we only allow activist reviews and shut down doctor's reviews, the probability of AIDS in all time periods goes down. Under the counterfactual exercise in which we only allow for the doctors' reviews, we find that the probability of AIDS increases, with a sharp increase between October 2002 and April 2004, followed by a drop in October 2006. This suggests that by opposing the doctor's review (and after controlling for objective drug qualities), patients are making choices that increase their probability of AIDS, especially so when good quality drugs are introduced (the probability of AIDS is highest between April 2002 and April 2004, when 3 new good quality drugs were introduced).[62]

At face value, the previous finding that patients are hurt when only doctors' reviews are available seems counterintuitive: they could be better off just by ignoring

[61] Notice that we are not estimating dynamic effects, but one-period-ahead simulations at different points in time. While estimating the dynamic effects is certainly of interest to us it is beyond the scope of this paper.

[62] We present details on how the state of the market evolves over time in Appendix C.5. Table C.20 shows the date of entry for the new drugs and their initial market share, and Table C.21 provides some summary statistics of the qualities and reviews for the new entrants at the time of entry and the *state of the market*. We can see that entrants are more effective compared to the market average (with the exception of the two early entrants), while some have fewer side effects but not all. Also note that while the doctors' reviews for the entrants are always higher (except for Atripla) than the market average, activists' reviews in some cases are lower.

the doctors' reviews instead of doing the opposite of what they say. Note, though, that patients also care about the likelihood of experiencing side effects. To investigate the effects on the latter, panel (b) of Figure C.10 shows that with only doctors' reviews available, the probability of no ailments goes up in all time periods. This shows that by not following doctors' reviews in informing treatment choice, patients are more likely to have AIDS but less likely to have side effects. Therefore, it seems that patients understand the basic trade off they face and have a greater preference for drugs which have lower side effects but are less effective. Another interesting finding is that with only activists' reviews available, there is an increase in the probability of no ailment, suggesting that activists' reviews push patients towards treatment choices that are more effective and do not cause severe side effects.[63]

3.5.3.3 Individual Characteristics and Demand for Expertise

Results until now suggest that patient responses to conflicting reviews could reflect their attempt to choose treatments with fewer side effects. Effective treatments with side effects are downgraded by the activist, but not by the doctor. Consumers with a distaste for side effects may understand this and utilize expertise accordingly.

[63] We also look at how the effects of reviews on health outcomes differ across individuals' health status. Our parameter estimates suggest that since individuals with AIDS follow the doctor's advice, and doctors are pushing drugs that are effective, we should expect to see a decrease in the probability of AIDS for this group. Figure C.11 presents the results for the sample of individuals who have AIDS in the current period. Figure C.11 (a) shows that when we only have doctor's reviews, even individuals with AIDS have a higher likelihood of suffering from AIDS in the next period. However, we find that once we control for composition effects (people with AIDS may differ in a systematic way in terms of their other sociodemographic characteristics), there is at least a 1.6% drop in the probability of AIDS when we only have the doctor's reviews, with a larger drop after April 2004, when there is a structural change in the market and new and effective drugs are introduced.

In particular, consumers may turn to the activist — a fellow patient whose review responds to side effects — when choosing treatments under uncertainty. A test for this explanation would consider the behavior of patients who are not necessarily seeking drugs with fewer side effects, but instead aim to use the most effective treatments possible.[64] Presumably, such patients would be more likely to follow the doctor's review. In fact, using the same data set, [110] shows that sicker patients are more willing to suffer side effects. The reason is that they face stronger incentives to make costly health investments and use treatments despite their drawbacks. If patient responses to reviews reflect a distaste for side effects, we might expect sicker patients to respond more positively to doctors' reviews in comparison to relatively healthy patients.

To explore this possibility, we allow parameters on reviews to depend on patient characteristics as formulated in equation (3.5). Results are presented in Table C.15. Many results are similar to baseline estimates. On average, individuals prefer combinations that have a higher probability of increasing CD4 count in the next period as well as those that increase the probability of suffering no ailments. The parameters on doctors' and activists' reviews are both statistically significant, showing that reviews matter for treatment choice.[65] As in the baseline model, a higher activist's review increases combo demand, while a higher doctor's review reduces demand.[66]

[64] Appendix C.1 presents a very simple theoretical model that formalizes the logic behind this falsification test.

[65] For the base case of a white individual with no AIDS, working part-time, less than college education, and who is taking the combination for the first time.

[66] Note, though, that we are already controlling for combos' objective characteristics. Therefore,

Turning to individual characteristics, we find that different types of patients react differently to reviews. The most striking finding is that sicker patients — defined as those living with AIDS — respond positively to both the doctor's and activist's reviews. In other words, for patients with AIDS, we find a reversal in sign in how patients respond to the doctor's review. While healthier patients respond positively to the activist and negatively to the doctor, sicker patients respond positively to both. This finding provides strong evidence of our preferred explanation of patient responses to conflicting reviews. When doctors and activists agree, their reviews lead to increases in demand for HIV treatments. When they disagree, healthier patients use information from the reviewer who downgrades effective treatment with harsh side effects. However, sicker patients who face strong incentives to invest in their health despite harsh side effects do the opposite. They utilize expertise from the doctor, the expert reviewer who recommends treatments based on their effectiveness and largely ignores side effects.

Interacting demand responses to expertise with individual characteristics provides several more nuanced lessons about how individuals incorporate possibly conflicting expert reviews into their decisions. We show that the coefficient on full-time work is negative and significant, meaning that full-time workers are more likely to avoid medication altogether. This is consistent with the idea that individuals may choose

when we say that the patient's preferences align with the activist's or do not align with the doctor's, this statement is conditional on objective characteristics. In other words, patient's preferences (do not) align with the activist's (doctor's) above and beyond objective effectiveness and side effects measures.

not to take life-saving treatments if the side-effects interfere with daily functions. Moreover, full-time work predicts a relatively large increase in demand due to a high activist's versus a high doctor's review. This suggests that full-time workers are somewhat more likely to use information from the activist, which makes sense if they aim to use treatments with fewer side effects.[67]

We also find evidence of differences by race in how consumers respond to expert reviews. In particular, our estimates suggest that black men are just as likely to follow the activist's review as are white men, but are less likely to follow the doctor. This is consistent with distrust of the medical establishment among African Americans, which has been documented in many studies [160]. A similar pattern emerges for individuals without a college degree: they place more weight on the activist's review. In other words, apart from health differences in how individuals respond to different sources of information, there may also be socioeconomic gradients. One concern with the pattern we find is that it suggests that lower-educated and non-white individuals may put their long-run health at more risk compared to white men with higher educations. Patients may follow the activist's review in an effort to use medical treatments that make side effects less probable. However, when they become ill, they

[67] The estimated positive coefficient on the dummy variable 'same combo last period - other', even though not significant, can be interpreted as capturing switching costs or, alternatively, as learning-by-doing (i.e., experience). That is, if a patient was taking a combo (other than the fringe) in the previous period, it is more likely that the patient will continue taking that same combo in the current period. On the other hand, if the patient was taking a combo from the fringe class in the previous period, it is more likely that the patient will switch out of the fringe in the current period. This could be interpreted as a cost associated with continuing experimenting with a rarely used treatment. The interactions also indicate that college-educated individuals respond positively and significantly to doctors' reviews, but not to activists' reviews.

turn to the doctor's review in an effort to recover their health. Indeed, following the activists review when in relatively good health makes most sense if patients switch gears when in poor health. If less educated or non-white individuals are less likely to switch to following the doctor's review when in poor health, they may be less likely to recover. If so, the expertise provided by the activist may be more harmful to blacks as compared to whites. If so, patient advocates (in our case, encapsulated in the activist's review) may provide information that is more helpful to more highly educated individuals at the expense of others. Future research could further explore how various information sources affect demand and health outcomes for different socioeconomic groups.

3.6 Conclusion

We have demonstrated that expert reviews affect demand in a high-stakes context: the market for HIV treatments. Much research on low-cost information and decision-making overlooks the idea that consumers often have access to multiple information sources. Exploiting rich data that includes objective drug qualities, individual-level health outcomes and multiple reviews, we show that consumer responses depend on their health along with other observable factors. We argue that these responses provide evidence that consumers demand information that is aligned to their preferences over health and side effects, which can vary depending on their current health state.

According to our results, consumers are not passive consumers of low-cost information sources, but actively incorporate information from different sources to make more informed decisions.

Future work could also compare consumer responses to conflicting reviews when reviews are side-by-side, as in our case, versus when they are not. For example, how consumers incorporate information into their choices could be different if acquiring additional information from a possibly conflicting source is costly. Moreover, future research could further explore heterogeneity in how individuals respond to various information sources when making decisions under uncertainty. An experimental setting could be used to vary not only the source of the information, but also its content. Moreover, though we have emphasized health differences in responses to doctors' versus activists' reviews, future work could focus on socioeconomic differences in how individuals respond to conflicting information sources. Such work could allow for an assessment of how such differences in the incorporation of information contribute to well-established health disparities.

Appendix A

Appendix for Chapter 1

A.1 Two Period Model

I develop a simple two period model to understand how an agent's labor supply decision responds to private school cost. I consider an economic environment which begins with the birth of a child with initial ability k_0. Period 1 child ability is a function of k_0 and mother's time with the child, m_1. In period 2, the mother chooses between sending her child to a public or private school. I define a variable s which is 1 if the child is sent to private school and 0 if the child goes to public school. Sending the child to private school incurs a cost p, while public schools are free of cost. Schooling is also added as an input to the second period child ability production function, in addition to mother's time with the child in period 2, m_2, and last period's child ability k_1. Let $h_t \in \{0, 1\}$ where $h_t = 1$ if the female works full-time and spends no time with the child, and $h_t = 0$ if the female does not work in period t. The female's maximization problem can then be written as:

$$V(c_1, c_2, k_1, k_2) = \underset{c_1, c_2, h_1, h_2, s}{max} U(c_1, k_1) + \beta U(c_2, k_2)$$

$$s.t$$

$$c_2 + sp = R(w_1 h_1 + N - c_1) + w_2 h_2, \tag{A.1}$$

$$k_1 = g_1(m_1, k_0), \tag{A.2}$$

$$k_2 = g_2(s, m_2, k_1), \tag{A.3}$$

$$1 = h_1 + m_1, \tag{A.4}$$

$$1 = h_2 + m_2. \tag{A.5}$$

where w_1 and w_2 is market wage in period 1 and 2, and N is non-labor income. Equation (A.1) is the female's inter-temporal budget constraint and equations (A.2) and (A.3) define the child ability production function in periods 1 and 2. I assume that utility is concave in all its arguments, and that

$$g_1(1, k_0) > g_1(0, k_0), \tag{A.6}$$

$$g_2(1, 1, g_1(1, k_0)) > g_2(0, 1, g_1(1, k_0)) = g_2(1, 0, g_1(1, k_0)) > g_2(0, 0, g_1(1, k_0)), \tag{A.7}$$

$$g_2(1,1,g_1(0,k_0)) = g_2(0,1,g_1(1,k_0)), \tag{A.8}$$

$$g_2(1,0,g_1(1,k_0)) > g_2(0,1,g_1(0,k_0)) > g_2(0,0,g_1(0,k_0)). \tag{A.9}$$

We can analyze eight cases derived from the two period theoretical model:

Case 1: $h_1 = 1, h_2 = 1, s = 1$

$$V^1(c_1,c_2,k_1,k_2) = U(c_1^{1*}, g_1(0,k_0)) + \beta U(R(w_1+N-c_1^{1*}) + w_2 - p, g_2(1,0,g_1(0,k_0))), \tag{A.10}$$

Case 2: $h_1 = 1, h_2 = 0, s = 0$

$$V^2(c_1,c_2,k_1,k_2) = U(c_1^{2*}, g_1(0,k_0)) + \beta U(R(w_1+N-c_1^{2*}), g_2(0,1,g_1(0,k_0))), \tag{A.11}$$

Case 3: $h_1 = 1, h_2 = 0, s = 1$

$$V^3(c_1,c_2,k_1,k_2) = U(c_1^{3*}, g_1(0,k_0)) + \beta U(R(w_1+N-c_1^{3*}) - p, g_2(1,1,g_1(0,k_0))), \tag{A.12}$$

Case 4: $h_1 = 1, h_2 = 1, s = 0$

$$V^4(c_1, c_2, k_1, k_2) = U(c_1^{4*}, g_1(0, k_0)) + \beta U(R(w_1 + N - c_1^{4*}) + w_2, g_2(0, 0, g_1(0, k_0))), \tag{A.13}$$

Case 5: $h_1 = 0, h_2 = 1, s = 1$

$$V^5(c_1, c_2, k_1, k_2) = U(c_1^{5*}, g_1(1, k_0)) + \beta U(R(N - c_1^{5*}) + w_2 - p, g_2(1, 0, g_1(1, k_0))), \tag{A.14}$$

Case 6: $h_1 = 0, h_2 = 1, s = 0$

$$V^6(c_1, c_2, k_1, k_2) = U(c_1^{6*}, g_1(1, k_0)) + \beta U(R(N - c_1^{6*}) + w_2, g_2(0, 0, g_1(1, k_0))), \tag{A.15}$$

Case 7: $h_1 = 0, h_2 = 0, s = 1$

$$V^7(c_1, c_2, k_1, k_2) = U(c_1^{7*}, g_1(1, k_0)) + \beta U(R(N - c_1^{7*}) - p, g_2(1, 1, g_1(1, k_0))), \tag{A.16}$$

Case 8: $h_1 = 0, h_2 = 0, s = 0$

$$V^8(c_1, c_2, k_1, k_2) = U(c_1^{8*}, g_1(1, k_0)) + \beta U(R(N - c_1^{8*}), g_2(0, 1, g_1(1, k_0))), \tag{A.17}$$

where c_1^{j*} is the solution to the first order condition with respect to c_1 for case j.

Within this simple framework, a number of testable propositions emerge which are consistent with the observed data patterns.

Proposition 1. *The mother will choose to work full-time and send her child to private school over not working and sending her child to public school if the marginal utility from the difference in consumption – which includes monetary investments in the child – is greater than the marginal utility from the difference in child cognition between the two scenarios.*

Proposition 2. *A drop in p unambiguously increases the likelihood of choosing private schooling for the child.*

Proposition 3. *An increase in p leads to an increase in end of period 1 savings.*

Proposition 4. *For women switching from public to private school (i.e. women at the school choice margin), or for women who have chosen private schooling for their child, an increase in p will increase female labor supply if the change in utility from lower consumption is more than the change in utility from higher child ability.*

A.1.1 Proofs

Proof of Proposition 1:

Proof. The proof can be generalized to any of the eight cases presented above. The female opts for case i versus case j, $j \neq i$, if and only if

$$V^i(c_1, c_2, k_1, k_2) - V^j(c_1, c_2, k_1, k_2) > 0, \tag{A.18}$$

$$= U(c_1^{*i}, c_2^{*i}, k_1^{*i}, k_2^{*i}) - U(c_1^{*j}, c_2^{*j}, k_1^{*j}, k_2^{*j}) > 0$$

$$= U(c_1^{*j} + \Delta c_1, c_2^{*j} + \Delta c_2, k_1^{*j} + \Delta k_1, k_2^{*j} + \Delta k_2) - U(c_1^{*j}, c_2^{*j}, k_1^{*j}, k_2^{*j}) > 0$$

$$\approx \frac{\partial U(c_1^{*j}, c_2^{*j}, k_1^{*j}, k_2^{*j})}{\partial c_1}\Delta c_1 + \frac{\partial U(c_1^{*j}, c_2^{*j}, k_1^{*j}, k_2^{*j})}{\partial c_2}\Delta c_2 + \frac{\partial U(c_1^{*j}, c_2^{*j}, k_1^{*j}, k_2^{*j})}{\partial k_1}\Delta k_1 + \frac{\partial U(c_1^{*j}, c_2^{*j}, k_1^{*j}, k_2^{*j})}{\partial k_2}\Delta k_2 > 0$$

where $c_1^{*k}, c_2^{*k}, k_1^{*k}$ and k_2^{*k} are the optimal values of consumption and child ability for case k. From equation (A.18), the female will choose case 1 over case 8 if and only if:

$$\frac{\partial U(c_1^{8*}, c_2^{8*}, k_1^{8*}, k_2^{8*})}{\partial c_1}[c_1^{1*} - c_1^{8*}] + \beta\frac{\partial U(c_1^{8*}, c_2^{8*}, k_1^{8*}, k_2^{8*})}{\partial c_2}[R(c_1^{8*} - c_1^{1*} + w_1) + w_2 - p] >$$
$$\frac{\partial U(c_1^{8*}, c_2^{8*}, k_1^{8*}, k_2^{8*})}{\partial k_1}[g_1(1, k_0) - g_1(0, k_0)] + \beta\frac{\partial U(c_1^{8*}, c_2^{8*}, k_1^{8*}, k_2^{8*})}{\partial k_2}[g_2(0, 1, g_1(1, k_0)) - g_2(1, 0, g_1(0, k_0))] \tag{A.19}$$

□

Proof of Proposition 2:

Proof. Let the difference between V^i and V^j, $j \neq i$, be:

$$D^i(c_1^i, c_2^i, k_1^i, k_2^i, c_1^j, c_2^j, k_1^j, k_2^j) = V^i(c_1, c_2, k_1, k_2) - V^j(c_1, c_2, k_1, k_2) \tag{A.20}$$

From the envelope theorem

$$\frac{\partial D^i(c_1^i, c_2^i, k_1^i, k_2^i, c_1^j, c_2^j, k_1^j, k_2^j)}{\partial p} = \beta\Big[(-1)\frac{\partial U^i(c_1^{i*}, c_2^{i*}, k_1^{i*}, k_2^{i*})}{\partial p} - \frac{\partial U^j(c_1^{j*}, c_2^{j*}, k_1^{j*}, k_2^{j*})}{\partial p}\Big] \tag{A.21}$$

where case j is any case in which the child goes to public school and case i is any case in which the child goes to private school. Since in this scenario $\frac{\partial U^j(c_1^{j*}, c_2^{j*}, k_1^{j*}, k_2^{j*})}{\partial p} = 0$, a decrease in p will lead to an increase in period 2 consumption, so that the probability of switching the child from public school to private school increases. In particular, the probability of switching from any case in which the child is going to public school (cases 2, 4 ,6 and 8), to any of the cases in which the child is going to private school (cases 1, 3, 5 and 7) increases when p decreases. □

Proof of Proposition 3:

Proof. The proof extends from equation (A.19). Specifically, when switching from any case in which the mother chooses public schooling for her child (cases 2, 4, 6 and 8) to any case in which the child is sent to private school, the mother will choose case 1,3 or 5 over case 7 (not working in either period and sending her child to private school) if and only if the marginal utility from the increase in child ability due to the mother spending time with the child in both periods is lower than the marginal utility from higher consumption due to labor market earnings. □

Proof of Proposition 4:

Proof. End of period 1 savings, $a_1^{k*} = w_1 h_1^{k*} + N - c_1^{k*}$, and $\frac{\partial a_1^{k*}}{\partial p} = -\frac{\partial c_1^{k*}}{\partial p}$. When p decreases, we would expect period 1 consumption to change by a non-negative number, which would lead to a decrease in savings □

A.1.2 Comparative Statics with respect to w_1, w_2, and N

Increase in w_1 and w_2

From the envelope theorem

$$\frac{\partial D^i(c_1^i, c_2^i, k_1^i, k_2^i, c_1^j, c_2^j, k_1^j, k_2^j)}{\partial w_1} = \beta\Big[\frac{\partial U^i(c_1^{i*}, c_2^{i*}, k_1^{i*}, k_2^{i*})}{\partial w_1} - \frac{\partial U^j(c_1^{j*}, c_2^{j*}, k_1^{j*}, k_2^{j*})}{\partial w_1}\Big] \tag{A.22}$$

where case j is any case in which the female does not work in period 1 while case i is any case in which $h_1 = 1$. Under this scenario, an increase in w_1 leads to an unambiguous increase in the probability of switching to cases in which the mother is working in period 1 i.e. cases 1, 2, 3 and 4, since $\frac{\partial U^j(c_1^{j*}, c_2^{j*}, k_1^{j*}, k_2^{j*})}{\partial w_1} = 0$ and an increase in period 1 earnings will lead to an increase in consumption, which raises the probability that the change in utility from higher consumption will exceed the loss in utility from lower child ability due to the mother spending less time with the child.

Conditional on working in the first period (cases 1-4), an increase in w_1 will increase period 1 and period 2 consumption, leading to an increase in the probability that the mother switches her child from public school to private school (since the extra earnings can be used for paying the higher school fee). Lastly, an increase in w_1 will increase period 1 savings if $\frac{\partial a_1^{k*}}{\partial w_1} = 1 - \frac{\partial c_1^{k*}}{\partial w_1} > 0$

Similarly, from the envelope theorem,

$$\frac{\partial D^i(c_1^i, c_2^i, k_1^i, k_2^i, c_1^j, c_2^j, k_1^j, k_2^j)}{\partial w_2} = \beta\Big[\frac{\partial U^i(c_1^{i*}, c_2^{i*}, k_1^{i*}, k_2^{i*})}{\partial w_2} - \frac{\partial U^j(c_1^{j*}, c_2^{j*}, k_1^{j*}, k_2^{j*})}{\partial w_2}\Big] \tag{A.23}$$

where case j is any case in which the female does not work in period 2 while case i is any case in which $h_2 = 1$. Under this scenario, an increase in w_2 will lead to an increase in the probability of switching to cases in which the mother is working in period 2 (cases 1, 4, 5 and 6), since $\frac{\partial U^j(c_1^{j*}, c_2^{j*}, k_1^{j*}, k_2^{j*})}{\partial w_2} = 0$ and an increase in period 2 earnings will lead to an increase in consumption, which raises the probability that the change in utility from higher consumption will exceed the loss in utility from lower child ability due to the mother spending less time with the child in period 2.

Conditional on working in period 2, an increase in w_2 will result in a non-negative change in period 1 and period 2 consumption, leading to an increase in the probability that the mother sends her child to a private school instead of a public school (since the extra period 2 earnings can be used to pay the private school fee). Finally, $\frac{\partial a_1^{k*}}{\partial w_2} = -\frac{\partial c_1^{k*}}{\partial w_2}$ i.e. savings will decrease if period 1 consumption increases as a result of w_2 rising.

Increase in N

From the envelope theorem, an increase in N will increase the probability of switching from case j to case i if and only if

$$\frac{\partial D^i(c_1^i, c_2^i, k_1^i, k_2^i, c_1^j, c_2^j, k_1^j, k_2^j)}{\partial N} = R\beta\Big[\frac{\partial U^i(c_1^{i*}, c_2^{i*}, k_1^{i*}, k_2^{i*})}{\partial N} - \frac{\partial U^j(c_1^{j*}, c_2^{j*}, k_1^{j*}, k_2^{j*})}{\partial N}\Big] > 0 \tag{A.24}$$

As an example, consider the choice between case 7 and case 8. The labor supply pattern of the mother is the same for both cases, and the only difference is the choice of private school in case 7. When N increases, c_1^{7*} and c_2^{7*} increases, which decreases the consumption gap between case 8 and 7, and increases the probability that the additional utility from higher child ability will exceed the change in utility from higher consumption in case 8. Lastly, an increase in N will increase savings if $\frac{\partial a_1^{k*}}{\partial N} = 1 - \frac{\partial c_1^{k*}}{\partial N} > 0$.

A.2 Data Appendix

I use data from two main sources: NLSY79 and NLSY79 Child and Young Adult, and supplement it with time use data from the Panel Study of Income Dynamics (PSID) and private school fee data from `privateschoolreview.com`. The NLSY79 Cohort is a longitudinal project that follows 12,686 American youth born between 1957-64, and were 14-22 year olds at the start of the survey. Around 52% of the individuals surveyed are women, and the survey was conducted annually through 1994, after which the survey was conducted on a biennial basis. The sample consists of a core random sample, and an oversample of blacks, Hispanics, poor whites and the military. Data is collected on respondents' schooling and employment, as well as marriage and fertility decisions. I use demographic data on the women of NLSY79 and construct the following key variables:

Labor Supply: NLSY79 collects data on annual hours worked by the respondent in the past calendar year. I use annual hours worked data to conduct analysis at the intensive margin. I also construct annual employment rates for each respondent for each year, where the respondent is counted as employed if she worked more than six weeks in the past calendar year.

Income: The NLSY reports the wage income and net family income in the past calendar year for each respondent. While total income from wages and salary in the past calendar year is self-reported, the net family income is a created variable, which is the sum of all sources of income for the family, including income from the spouse, farm income as well as welfare income.

Assets: NLSY started collecting data on savings and assets from 1985. The savings variable is an indicator variable which is an answer to whether the respondent or respondent's spouse has any cash kept in a safe place at home, or money in a savings or checking accounts, money market funds, credit unions, U.S. savings bonds, Individual Retirement Accounts (IRA or Keogh), certificates of deposit, personal loans to others or rights to an estate or an investment trust. In a follow-up question, respondents are asked the total amount of money assets altogether in these instruments. NLSY also contains a created variable on family net worth, that is available from 1985 onwards, and is constructed by summing all asset values and subtracting all debts. Missing assets and debt values are imputed.

Child's Schooling and Test Scores: A separate survey of all children born to the NLSY79 female respondents began in 1986, in which children were followed from the time of their birth. In addition to all the mother's information from NLSY79, the child survey includes information about the child's schooling, as well as demographic and development information collected from the mother and the child. In particular, the NLSY79 Child and Young Adult (C-NLSY79) survey contains information about the type of school the child studies in, which helps identify whether the child is going to a public school or private school. Additionally, C-NLSY79 also reports cognitive assessment scores for each child in the survey. I use the standardized scores on the Peabody Picture Vocabulary Test (PPVT), Peabody Individual Achievement

Test-Reading Recognition subtest (PIAT-R) and the Peabody Individual Achievement Test - Mathematics subtest (PIAT-M) as measures of child's cognitive ability. Standardized scores are an age-specific transformation of the raw scores. The PPVT is a vocabulary test for standard American English and provides a quick estimate of verbal ability and scholastic aptitude for children less than 5 years of age. The PIAT-M measures attainment in mathematics. Finally the PIAT-R measures word recognition and pronunciation ability.

Time Use Data: Though NLSY79 and C-NLSY79 are a rich source of data on labor supply, wages and child development, it does not collect time use data for parents and children. To supplement data from NLSY79, I use time diary data from the Panel Study of Income Dynamics (PSID) Child Development Supplements (CDS-I and CDS-II). The PSID is a longitudinal dataset of a nationally representative sample of about 5000 American families that was started in 1968. In 1997, the PSID began collecting data for up to two children from a random sample of families that had children under the age of 13 in the Child Development Supplement (CDS-I). A follow-up survey was conducted in 2002-3 (CDS-II), when children were between 8-18 years of age. The entire CDS sample consists of 3,500 children residing in 2,400 families. The CDS collects extensive data on child development and time use. For two days per week (one weekday and either Saturday or Sunday), children (young children were aided by a primary care giver) filled out a detailed 24 hour time diary in which they recorded all activities during the day and who else (if anyone) participated with the child in these activities. At any point in time, the children recorded the intensity of participation for both parents. Parents could either be actively involved (active time use), or just be around without being engaged in any activity with the child (passive time use). I construct annual time use measures for the mother by summing both active and passive time for a day, multiplying the daily hours by 5 for the weekday and 2 for the weekend day to get a weekly measure (using a Saturday and Sunday report adjustment) and then multiplying by 52 for the annual measure.

Private School Fee: State level tuition data is obtained from `privateschoolreview.com`, a website that lists private schools in each state, gives information about the average tuition at the state and national level, as well as information on average acceptance rates, student body demographics and teacher student ratios. The website also hosts articles for parents on why they should send their child to private schools, and if they choose to do so, how they can pay for it. Data on tuition is available at the state level only for the school year 2014-2015. I extrapolate data for my sample years, I adjust the fee data by inflation.[1]

Construction of the Private School Variable

In order to construct the private school dummy, I use the question in which respondents are asked of the type of school their child goes to. The respondents can

[1] Adjusting the 2014-2015 tuition data for inflation can be concerning since private school tuition rose more than inflation in the 1990s and 2000s. While I use the inflation-adjusted tuition data for the reduced-form analysis, I allow for measurement error in private school tuition data in the structural model.

choose between private school, public school, home schooling and no school. This question was added to the NLSY79 after 1998, therefore, for some children, information about school type is available when they are older than 4-6 years of age (when children start primary school).

The private school variable is meant to capture the preference for better schooling and additional cost associated with it. I let the private school dummy to be 1 if the mother of the child has ever reported that her child goes to private school. This means that mothers of children who ever went to a private school (even if they, at some point, were going to a private school and switched to a private school, or vice versa), are coded as "private school mothers".

There are a total of 39 children who switch schools. Out of these 39 children, 9 switch from a private school at younger ages to public school when they are 12 or older, while the remaining 30 children switch from a public school to a private school. The ages of children for whom this question is answered for the first time range from 4 years of age till 14 years of age, so that the maximum extrapolation about child's school type is 8 years, which happens for 151 children (8.68% of individuals who respond to this question)). 71% of the children for whom this information is available for the first time are less than 12 years of age.

Construction of the Aggregate Test Score

The PPVT is available for children who between four and five years of age, while the PIAT-R and PIAT-M are available for children of age five and above. There are, however, cases in which all three test scores are not available for the child. To avoid losing any information due to missing values, I follow [24] and pool the three test scores available by averaging across all three age-adjusted standardized test scores.

A.3 Additional Results from Preliminary Analysis

I report additional descriptive statistics and regression results of the impact of private schooling decision on annual hours worked, probability of being employed and the probability of having savings. For the labor market results, I report the marginal effects of choosing private school for different sub-populations by stratifying on education and non-labor income quantiles.

A.3.1 Descriptive Statistics

Table A.9 shows that among the more educated mothers, a higher proportion send their child to private schools and that private school enrollment is higher among households with higher family income.[2] I also find the proportion of people who are sending their children to a private school in each county. In my NLSY79 sample, the counties with highest private school enrollment are Alexandria City, Virginia; Baltimore, Maryland; Hamilton, Indiana; Hamilton, Ohio and St. Joseph, Indiana.[3]

[2]In the sample, non-labor income is distributed as follows: Quantile 1: $\leq$ \$6,207, Quantile 2: Between \$6,208 and \$21,384, Quantile 3: Between 21,385 and \$36,731, and Quantile 4: Between \$36,732 and \$1,167,736.

[3]Note that in order to calculate the proportion of children going to private school in each county, I exclude counties where less than 50 people are residing in my sample. I am also aggregating individuals over all years.

A.3.2 Auxiliary Regressions

To capture the dynamics of maternal labor supply, I interact private school choice with six different periods of the female's life cycle: (1) 4-6 years before the child is born, (2) 1-3 years before the child is born, (3) 0-2 years after childbirth, (4) 3-5 years after childbirth, (5) 6-8 years after childbirth, and (6) 9-11 years after childbirth. Table A.10 presents the results of the average marginal effect of choosing private schooling over different periods of the mother's life cycle. The results mirror the patterns observed in the graphical analysis. Even after controlling for mother's education, non-labor income, and state fixed effects, I find that private school mothers are working significantly more before the child is born, and significantly less than public school mothers after childbirth.

Table A.11 presents marginal effects of private schooling at the extensive margin. On average, the probability of being employed 4-6 years before birth is 5% higher for private school mothers, while after the child starts school, private school mothers are 9.3% less likely to be working. In Table A.12 and Table A.13, I present results for the marginal effect of choosing private schooling on the probability of having savings and asset holdings of females. After controlling for demographic, education and geographic controls that may affect the assets that households accumulate, I find that the probability of having savings 4-6 years before child's birth is 8.1% higher for private school mothers, and is 3.8% higher just before the child is about to start private schooling. I also find that asset holding of private school mothers is higher after the first two years of child's birth.

Finally, in Table A.14, I show how the labor supply and savings response of women belonging to different education and non-labor income sub-groups. The first column shows that for all values of non-labor income, private school mothers with lower education levels work more hours annually when the child is 3-8 years of age and work less after the child is 3 years of age as their education level rises. This is consistent with the graphical evidence presented earlier, which showed that private school mothers with less than a high school degree were working more hours that public school mothers, but more educated mothers were spending more time with their children after 3 years of age. Columns 2 and 3 show that higher educated private school mothers at all levels of non-labor income do hold more assets just before the child is about to start school.

A.4 Additional Results for Structural Estimation

This section presents additional results from the structural estimation. Section C.3 presents the algorithm employed for the Bayesian estimation. Next, I show additional results for goodness of fit.

A.4.1 Solution Method for Structural Estimation

This section describes the [50] Bayesian estimation algorithm. The fundamental idea behind the algorithm is to not only treat the parameters but also the value functions and expected value functions as objects that have to be updated at each Monte Carlo Markov Chain (MCMC) iteration. The algorithm consists of three steps:

1. **The Parameter Updating Step (Metropolis-Hastings algorithm)**:

   First, draw a candidate parameter vector from the proposal density $\Theta^{(s)*} \sim q(\Theta^{(s)*}|\Theta^{(s)})$, where $\Theta^{(s)}$ is the parameter at the s^{th} iteration, and q is assumed to follow the Gaussian distribution centered at $\Theta^{(s)}$. Then, evaluate the Method of Simulated Moments objective function $\mathcal{G}(\Theta) = (M_N - M_S(\Theta))' W_N (M_N - M_S(\Theta))$ conditional on $\Omega^{(s)*}$ and conditional on $\Theta^{(s)}$. Now, form the acceptance probability

$$P = \min\left\{ \frac{\mathcal{G}(\Theta^{(s)} q(\Theta^{(s)*}|\Theta^{(s)})}{\mathcal{G}(\Theta^{(s)*} q(\Theta^{(s)}|\Theta^{(s)*})}, 1 \right\}. \tag{A.25}$$

   We then accept $\Theta^{(s)*}$ with probability P, i.e.

$$\Theta^{(s+1)} = \begin{cases} \Theta^{(s)*} & \text{with probability} \quad P \\ \Theta^{(s)} & \text{with probability} \quad 1 - P. \end{cases}$$

2. **The Dynamic Programming (or Bellman equation iteration) Step**:

   The following Bellman equation step is nested within the parameter updating step (individual subscripts are suppressed for ease of notation):

$$V_t^{(s)}(\Omega_t^{phase}, \Theta^{(s)}) = max_{\mathcal{D}}(V_t^{1(s)}(\Omega_t^{phase}), \ldots, V_t^{ns(s)}(\Omega_t^{phase})), \tag{A.26}$$

$$V_t^{k(s)}(\Omega_t^{phase}, \Theta^{(s)}) = U_t^k(\Omega_t^{phase}, \Theta^{(s)}) + \beta \widehat{E^{(s)}}\Big[V_{t+1}(\Omega_{t+1}^{phase}, \Theta^{(s)})|\Omega_t^{phase}, \mathcal{D} = k\Big], \quad k = 1, \ldots, n \tag{A.27}$$

where $\mathcal{D}$ is the choice tuple at time t, k indexes the choice, and ns is the number of choices in period t.

3. **Expected Value Approximation Step**:

The expected value function approximation is computed using information from earlier iterations of the MCMC algorithm. The idea is to approximate the expected value functions at $\Theta^{(s)}$ by looking at value functions that were already calculated on earlier iterations of the MCMC algorithm, emphasizing parameter values that are ?close? to $\Theta^{(s)}$. Specifically, the expected value function is approximated as:

$$\widehat{E^{(s)}}\Big[V_{t+1}(\Omega_{t+1}^{phase}, \Theta^{(s)})|\Omega_t^{phase}, \mathcal{D} = k\Big] = \frac{1}{N^{(s)}} \sum_{j=1}^{N^{(s)}} V^{(j)}(\Omega_{t+1}, \Theta^{(j)}) W(\Omega_{t+1}, \Theta^{(j)}), \tag{A.28}$$

where $\Theta^{(j)}$ denotes a parameter value from an earlier iteration (j) of the MCMC algorithm and $V^{(j)}(\Omega_{t+1}, \Theta^{(j)})$ is the value function at state point Ω_{t+1} that was calculated on iteration (j).[4] Finally, $W(\Omega_{t+1}, \Theta^{(j)})$ is a weighting function that

[4] Note that in equation (A.28) I only have a single sum over iterations because in an abuse of

formalizes the notion of closeness between $\Theta^{(s)}$ and $\Theta^{(j)}$. I follow [50] and define the weighting function as:

$$W(\Omega_{t+1}, \Theta^{(j)}) = \frac{K_h(\Theta^{(j)}, \Theta)}{\sum_{m=1}^{N(s)} K_h(\Theta^{(m)}, \Theta)}, \tag{A.29}$$

where K_h is a kernel with bandwidth $h = 0.02$.

As the number of iterations grows large, the output of this algorithm generates convergence to the posterior distribution of the parameter vector, as well as convergence to the correct (state and parameter contingent) value functions. I initialize the algorithm using an arbitrary vector of starting values. Therefore, the sum in eq (A.28) needs to be taken on a moving window of more recent iterations. I solve the full model (with value function iterations) for the first 2000 "burn-in" iterations, and then start the expected value approximation. I use a moving window of the last 100 iterations to calculate the sum in eq (A.28). I also solve the full model after every 100 iterations to ensure the approximation is not far away from the true value function.

A.4.2 Results

Table A.15 (a) reports logit coefficients used to calculate the transition probability for having a child in the next period. Estimates show that the probability of having a

notations, I am letting the expression inside the sum to represent the expected value function at $t + 1$, where the expectation is taken over the stochastically evolving state space (in my model, number of children, marital status and child ability in the next period evolve stochastically).

child goes down as a woman's age increases. However, compared with women who are high school dropouts, women belonging to higher education groups are more likely to have a child. Blacks and married women are also more likely to have child in the next period. Table A.15 (b) reports the logit coefficients for calculating the probability of entering into marriage conditional on being unmarried in the last period. Estimates show that the probability of marriage increases with education, but goes down with age and is also lower for blacks as compared to white and hispanic women. The probability of being married is also lower for women who have a child greater than six years of age. Finally, Table A.15 (c) shows that the probability of transitioning out of marriage increases with age, is higher for blacks, and goes down as education of the mother increases, and is higher if the woman has a child greater than six years of age.

A.5 Tables

Table A.1: Summary Statistics

	Public					Private				
	Mean	S.d	Min	Max	N	Mean	S.d	Min	Max	N
Hispanic	0.07	0.26	0	1	59304	0.05	0.22	0	1	16839
Black	0.13	0.34	0	1	59304	0.06	0.23	0	1	16839
White	0.80	0.40	0	1	59304	0.89	0.31	0	1	16839
Urban	0.75	0.43	0	1	55447	0.84	0.37	0	1	15568
Protestant	0.05	0.21	0	1	59114	0.06	0.24	0	1	16795
Baptist	0.20	0.40	0	1	59114	0.12	0.32	0	1	16795
Episcopalian	0.02	0.12	0	1	59114	0.03	0.19	0	1	16795
Lutheran	0.07	0.25	0	1	59114	0.04	0.20	0	1	16795
Methodist	0.08	0.27	0	1	59114	0.05	0.23	0	1	16795
Presbyterian	0.03	0.17	0	1	59114	0.04	0.20	0	1	16795
Roman Catholic	0.31	0.46	0	1	59114	0.43	0.50	0	1	16795
Jewish	0.02	0.13	0	1	59114	0.03	0.17	0	1	16795
Other Religions	0.14	0.35	0	1	59114	0.14	0.34	0	1	16795
Less than High School	0.14	0.34	0	1	59304	0.02	0.14	0	1	16839
High School	0.41	0.49	0	1	59304	0.25	0.43	0	1	16839
College	0.26	0.44	0	1	59304	0.23	0.42	0	1	16839
More than College	0.19	0.39	0	1	59304	0.50	0.50	0	1	16839
Age	30.0	7.92	18	53	57532	30.6	8.42	18	53	16190
Age at First Marriage	23.4	4.34	18	50	58946	25.0	4.38	18	46	16778
Age at First Birth	22.9	4.06	13	40	43309	26.2	4.43	13	41	9655
No. of Children	2.82	1.19	1	10	59304	2.88	1.35	1	10	16839
Child Age	7.92	5.78	0	18	37512	7.77	5.55	0	18	8161
Child Care 1^{st} year	0.48	0.50	0	1	56693	0.48	0.50	0	1	15652
Child Care 2^{nd} year	0.52	0.50	0	1	55849	0.54	0.50	0	1	14956
Child Care 3^{rd} year	0.54	0.49	0	1	55048	0.54	0.50	0	1	14873
Annual Wage Income	13.2	12.8	0	194.04	44011	17.6	20.2	0	194.04	13769
Annual Family Income	42.0	64.7	0	1168.3	48281	68.9	108.5	0	1168.3	13629
Annual Non-labor Income	29.6	56.7	-71.5	1167.8	38207	49.2	97.2	-71.9	1167.5	11871
Spouse's Annual Earnings	32.3	26.5	0	219.78	29040	48.3	42.0	0	219.8	8989
Total Assets	28.6	146.2	0	5955.6	23506	58.6	221.3	0	4637.1	8394
Net Worth	75.8	190.4	-1015	2093.2	35259	148.5	283.2	-605.1	2093.3	9672
Annual Hours	1237.9	932.8	0	8736	56858	1287.1	928.1	0	7950	15985
Annual Employment Rate	0.78	0.41	0	1	56858	0.81	0.39	0	1	15985
Full-time Work	0.43	0.50	0	1	56858	0.45	0.50	0	1	15985
Part-time Work	0.35	0.48	0	1	56858	0.36	0.48	0	1	15985
No Work	0.22	0.41	0	1	56858	0.19	0.39	0	1	15985
Spouse's Annual Hours	2198.2	677.5	0	8736	34409	2325.1	675.9	0	8736	10172
PIAT - Math	103.7	13.6	65	135	9,528	109.2	12.2	65	135	1,752
PIAT - Reading Recognition	106.6	14.4	65	135	9,481	112.0	12.1	65	135	1,749
PPVT	96.9	18.2	0	158	6,215	105.2	17.5	20	158	687
Test Score	219.7	81.0	0	424	11,748	261.9	59.1	95	428	1,756
Private School Fee						8.96	3.87	2.13	26.82	76143

Notes: Family Income, Wage Income, Non-labor Income, Spouses' Annual Earnings, Total Assets, Net Worth and Private School Fee are in constant 1990 dollars (using the Bureau of Labor Statistics Consumer Price Index - All Urban Consumers (CPI-U)). The values have also been divided by 1000. All summary statistics are weighted using the sampling weights provided by NLSY79. Annual Employment Rate reports the average of a dummy which is 1 if the respondent has worked more than 6 weeks in the past calendar year. The respondent is considered as having worked full-time if she worked more than 1600 hours in the past calendar year, part-time if she worked less that 1600 hours but more than 6 weeks, and unemployed (no work) if she worked less than or equal to 6 weeks in the past calendar year.

Test Score is a composite measure of test score for the children of NLSY79, which is created by averaging over the standardized PIAT-Math, PIAT-Reading Recognition and PPVT scores.

Table A.2: DESCRIPTIVE REGRESSIONS

	Private	Annual Hours			Employment Rate		
		(1)	(2)	(3)	(1)	(2)	(3)
Private			-13.7	-38.1***		-0.10***	-0.15***
			(10.3)	(10.8)		(0.02)	(0.03)
Age	0.14***	207.3***		208.3***	0.28***		0.29***
	(0.00)	(4.41)		(4.42)	(0.011)		(0.011)
Age Square		-2.76***		-2.76***	-0.01***		-0.01***
		(0.07)		(0.07)	(0.00)		(0.00)
Married	0.01	-86.3***		-86.2***	-0.09***		-0.09***
	(0.02)	(9.63)		(9.64)	(0.025)		(0.03)
No. of Children	0.03***	-190.2***		-189.9***	-0.17***		-0.17***
	(0.01)	(4.81)		(4.81)	(0.010)		(0.01)
Child Age	-0.15***	5.46***		3.81***	0.01		-0.00
	(0.00)	(1.18)		(1.26)	(0.003)		(0.00)
Hispanic	0.26***	39.3***		40.8***	0.05		0.05
	(0.03)	(14.8)		(14.9)	(0.035)		(0.04)
White	0.39***	-73.1***		-70.2***	0.11***		0.13***
	(0.02)	(11.7)		(11.7)	(0.03)		(0.03)
High School	0.62***	191.0***		195.0***	0.30***		0.32***
	(0.03)	(14.9)		(15.0)	(0.031)		(0.031)
College	0.81***	140.2***		146.0***	0.39***		0.42***
	(0.03)	(15.5)		(15.5)	(0.03)		(0.04)
More than College	1.05***	190.5***		199.6***	0.47***		0.51***
	(0.04)	(17.8)		(18.0)	(0.04)		(0.04)
Non-Labor Income	0.01***	-7.90***		-7.77***	-0.02***		-0.015***
	(0.00)	(0.95)		(0.94)	(0.001)		(0.00)
Urban	0.18***	-19.3*		-17.7*	-0.01		0.00
	(0.02)	(10.5)		(10.5)	(0.03)		(0.03)
Protestant	0.12**	-37.1		-35.9	-0.06		-0.05
	(0.05)	(25.1)		(25.0)	(0.06)		(0.06)
Baptist	0.15***	157.4***		159.3***	0.07*		0.08*
	(0.04)	(17.8)		(17.8)	(0.04)		(0.04)
Episcopalian	0.28***	100.1***		103.2***	-0.014		-0.00
	(0.06)	(37.4)		(37.4)	(0.09)		(0.09)
Lutheran	-0.11**	173.6***		172.7***	0.36***		0.35***
	(0.05)	(21.6)		(21.6)	(0.07)		(0.07)
Methodist	-0.05	83.9***		83.6***	0.08		0.08
	(0.05)	(20.9)		(20.9)	(0.05)		(0.05)
Presbyterian	0.42***	76.6***		80.8***	0.20***		0.21***
	(0.05)	(26.1)		(26.1)	(0.08)		(0.08)
Roman Catholic	0.42***	76.2***		80.3***	0.11***		0.13***
	(0.04)	(16.8)		(16.8)	(0.04)		(0.04)
Jewish	0.08	-102.6**		-101.9**	-0.11		-0.10
	(0.07)	(42.4)		(42.6)	(0.10)		(0.10)
Other religions	0.35***	64.2***		67.6***	0.01		0.02
	(0.04)	(19.1)		(19.1)	(0.05)		(0.05)
N	47842	47842	47842	47842	47842	47842	47842

Notes: The dependent variables for each column, respectively, are: 1) An indicator variable for whether the respondent sends her child to a private school, 2) Annual hours worked by the respondent, and 3) an indicator variable for whether the respondent worked more than 6 weeks in the past calendar year. Total Assets, Wage Income, Non-Labor Income and Family Income have been divided by 10,000 and have been converted to constant 1990 dollars using BLS Consumer Price Index - Urban Workers (CPI-U). * $p < 0.10$,** $p < 0.05$, ***$p < 0.01$; standard errors are given in parentheses.

Table A.3: State Space

Variable	Description	Phase 1	Phase 2	Phase 3
(a) Time-invariant				
$educ_i$	Female's education level	✓	✓	✓
$race_i$	Female's race	✓	✓	✓
μ_i	Female's unobserved type	✓	✓	✓
(b) Time-varying				
A_{it}	Asset stock available at start of period t	✓	✓	✓
H_{it}	Stock of human capital at start of period t	✓	✓	✓
k_{it}	Child's cognitive ability in period t	✗	✓	✓
m_{it}	Marital status	✓	✓	✓
n_{it}^k	No. of children	✓	✓	✓
y_{it}	Husband's income	✓	✓	✓
a_{it}^k	Child's age	✗	✓	✓
p_{it}	Private school fee	✗	✗	✓
Ψ	Vector of iid shocks to preferences	✓	✓	✓
ξ_{it}	Idiosyncratic shock to female's wage	✓	✓	✓
ξ_{it}^f	Idiosyncratic shock to husband's earnings process	✓	✓	✓
η_{it}	Idiosyncratic shock to child ability	✓	✓	✓

Notes: The table lists all state space variables and their description. The checkmarks indicate the phases in which the variable is part of the state space.

Table A.4: Preference Parameters

Parameter	Variable	Estimate	Std. Error	Parameter	Variable	Estimate	Std. Error
(a) Private School Preference Parameters				(e) Initial Child Ability			
γ_0^s	Constant	0.265	0.018	$\gamma_0^{k_0}$	Constant	1.493	0.935
γ_{12}^s	High School	0.130	0.037	$\gamma_{12}^{k_0}$	High School	0.648	0.144
γ_{13}^s	Some College or Greater	0.474	0.087	$\gamma_{13}^{k_0}$	Some College or More	0.611	0.201
γ_2^s	No. of children	0.015	0.018	$\gamma_2^{k_0}$	Black	-0.063	0.093
γ_{31}^s	Type 1	-0.764	0.448	$\gamma_{31}^{k_0}$	Type 1	-0.090	0.201
γ_{32}^s	Type 2	-0.246	0.313	$\gamma_{32}^{k_0}$	Type 2	0.033	0.002
γ_{33}^s	Type 3	0.114	0.056	$\gamma_{33}^{k_0}$	Type 3	0.425	0.071
(b) Consumption Preference Parameters				(f) Child Ability Production Function			
α_1	CRRA parameter	0.354	0.064	β_0	Total Factor Productivity	0.781	0.514
γ_0^c	Constant	0.585	0.076	β_1	$\ln k$	0.013	0.005
γ_1^c	Child age < 6	-0.091	0.016	β_3	$\ln G$	0.990	0.085
γ_2^c	Child age ≥ 6	0.089	0.010	β_4	s	0.042	0.014
γ_{32}^c	High School	0.404	0.115	β_5	$\ln k \times \ln \tau$	0.010	0.033
γ_{33}^c	Some College or More	0.602	0.045	β_6	$\ln k \times \ln G$	-0.010	0.009
γ_4^c	No. of children	0.307	0.202	β_7	$\ln \tau \times \ln G$	0.069	0.029
γ_{51}^c	Type 1	0.451	0.041	β_8	$\ln k \times s$	0.002	0.006
γ_{52}^c	Type 2	0.062	0.008	β_9	$\ln \tau \times s$	0.153	0.093
γ_{53}^c	Type 3	0.141	0.023	β_{10}	$\ln G \times s$	0.004	0.001
(c) Child Ability Preference Parameters				(g) Productivity of Mother's Time			
λ	CRRA parameter	0.489	0.116	π_0^τ	Constant	0.431	0.857
γ_0^k	Constant	-0.133	0.782	π_1^τ	Child age < 6	0.746	0.223
γ_1^k	Child age < 6	2.902	1.451	π_2^τ	Child age ≥ 6	0.399	0.351
γ_2^k	Child age ≥ 6	2.001	1.347	π_{32}^τ	High School	0.232	0.250
γ_{32}^k	High School	1.014	0.418	π_{33}^τ	Some College or More	0.227	0.101
γ_{33}^k	Some College or More	1.058	0.458	π_4^τ	Married	0.045	0.052
γ_4^k	No. of children	-0.015	0.161	π_5^τ	No. of Children	0.116	0.082
γ_5^k	Married	0.889	0.305	π_{61}^τ	Type 1	-0.209	0.803
γ_{61}^k	Type 1	0.321	0.554	π_{62}^τ	Type 2	-0.348	0.509
γ_{62}^k	Type 2	0.347	0.819	π_{63}^τ	Type 3	0.536	0.081
γ_{63}^k	Type 3	0.504	0.177	σ_η^2	Variance of ability shock	0.805	0.336
(d) Leisure Preference Parameters				(h) Type Parameters and Type Distribution			
γ_0^h	Constant	0.416	0.240	α_{02}^μ	Type 1 Constant	0.309	0.151
γ_1^h	Child age < 6	-2.727	0.856	α_{112}^μ	Type 1 High School	0.426	0.308
γ_2^h	Child age ≥ 6	3.729	1.704	α_{122}^μ	Type 1 Some College or More	0.195	0.024
γ_{32}^h	High School	0.240	0.103	α_{03}^μ	Type 3 Constant	-0.172	0.244
γ_{33}^h	Some College or More	0.336	0.032	α_{113}^μ	Type 3 High School	-0.006	0.004
γ_4^h	No. of children	0.546	0.120	α_{123}^μ	Type 3 Some College or More	0.335	0.080
γ_{51}^h	Type 1	0.064	0.018	π_{μ_1}	Proportion of Type 1	0.471	
γ_{52}^h	Type 2	0.186	0.564	π_{μ_2}	Proportion of Type 2	0.267	
γ_{53}^h	Type 3	0.044	0.034	π_{μ_3}	Proportion of Type 3	0.262	

Notes: The table reports preference parameters for the method of moment estimation. Standard errors are calculated by solving the model using the Monte Carlo Markov Chain method 50 times and using those 50 estimates to calculate the variance of the parameters.

Table A.5: Budget Constraint Parameters

Parameter	Variable	Estimate	Std. Error
(a) Wage Parameters			
γ_0^w	Constant	0.992	0.108
γ_{11}^w	High School	0.002	0.097
γ_{12}^w	Some College or More	0.458	0.217
γ_2^w	Black	-0.114	0.034
γ_3^w	Experience	0.102	0.013
γ_4^w	Experience Squared	-0.001	0.006
γ_{51}^w	Type 1	0.022	0.053
γ_{52}^w	Type 2	0.340	0.168
γ_{53}^w	Type 3	0.825	0.086
σ_ξ^2	Wage shock variance	0.170	0.020
(b) Husband's Weekly Earnings Parameters			
$\gamma_0^{y^h}$	Constant	336.6	50.15
$\gamma_{11}^{y^h}$	High School	684.4	230.8
$\gamma_{12}^{y^h}$	College and More	461.9	123.4
$\gamma_2^{y^h}$	Black	-48.95	50.15
$\gamma_3^{y^h}$	t	393.1	162.5
$\gamma_4^{y^h}$	t squared	-0.160	0.016
$\gamma_{51}^{y^h}$	Type 1	319.0	708.2
$\gamma_{52}^{y^h}$	Type 2	300.6	33.60
$\gamma_{53}^{y^h}$	Type 3	-104.4	15.11
$\sigma_{\xi^h}^2$	Earnings shock variance	73.17	45.49
(c) Asset Evolution and Terminal Value Parameters			
$\underline{b}$	Assets lower bound	$-\$41,520$	51547
$\underline{c}$	Consumption lower bound	\$164	90.1
cost	Cost of other kids	3,903	1406
α_G	Proportion of family income	0.03	0.002
α^p	School fee intercept	3.245	2.713
β^p	School fee slope	0.822	0.259
σ_p^2	School fee error variance	0.307	0.235
γ_1^T	Value from assets in T	0.004	0.001
γ_2^T	Value from k in T	1.726	0.606

Notes: The table reports female's wage and husband's weekly earnings parameters, as well as the asset evolution equation parameters for the Method of Moment estimation. Standard errors are calculated by solving the model using the Monte Carlo Markov Chain method 50 times with different starting values and using those 50 estimates to calculate the variance of the parameters.

Table A.6: Impact of Drop in Private School Fee

(a) 25% Decrease

	Full Sample			New Entrants			Incumbents		
	Baseline	Subsidy	%Δ	Baseline	Subsidy	%Δ	Baseline	Subsidy	%Δ
Private School	0.27	0.30	+11.1						
Log Ability	7.27	7.65	+5.2	1.76	7.60	+332	9.21	9.21	0.00
Hours with Child	431.8	431.4	-0.01	591.1	566.0	-4.23	388.6	388.4	-0.04
Hours Worked (cond. on working)	1319	1337	+1.4	1047	2064	+97.1	2064	2052	-0.58
Terminal Assets	81.7	84.2	+3.1	12.9	18.5	+43.4	45.8	46.3	+0.91
Mean Wages	12.7	12.3	-3.15	6.34	7.71	+21.6	7.08	7.07	-0.11

(b) 75% Decrease

	Full Sample			New Entrants			Incumbents		
	Baseline	Subsidy	%Δ	Baseline	Subsidy	%Δ	Baseline	Subsidy	%Δ
Private School	0.27	0.50	+85.2						
Log Ability	7.27	7.67	+5.5	5.04	6.49	+28.7	9.21	9.20	-0.04
Hours with Child	431.8	441.5	+2.25	550.6	592.0	+7.52	388.7	390.7	+0.51
Hours Worked (cond. on working)	1319	1293	-1.97	1168	1103	-5.57	2064	1106	-46.4
Terminal Assets	81.7	80.5	-0.01	84.8	80.6	-4.95	45.8	45.2	-1.45
Mean Wages	12.7	12.3	-3.15	13.0	12.1	-6.90	7.05	6.89	-2.27

Notes: The table reports changes in life cycle outcomes under counterfactual scenarios with universal subsidies. Panel (a) reports results for the experiment in which everyone gets a 25% subsidy. Panel (b) reports results for the experiment in which everyone gets a 75% subsidy. Baseline results are averages with estimated parameters and observed private school fee in the data. Results for log ability, assets and mean wages are calculated for period 25 (terminal period). Results for private schooling, hours with child and hours worked are calculated by averaging over all time periods.

Table A.7: Subsidy with Asset Test

	Full Sample			New Entrants			Incumbents		
	Baseline	Subsidy	%Δ	Baseline	Subsidy	%Δ	Baseline	Subsidy	%Δ
Private School	0.27	0.43	+56.2						
Log Ability	7.27	7.29	+0.28	5.80	5.86	+1.03	9.21	9.18	-0.33
Hours with Child	431.8	429.1	-0.63	545.9	529.6	-6.69	388.5	388	+2.83
Hours Worked (cond. on working)	1319	1362	+3.27	1175	1456	+23.9	2063	1633	-20.8
Terminal Assets	81.7	87.7	+7.34	60.3	87.9	+45.8	45.8	46.9	+2.36
Mean Wages	12.70	12.73	+0.24	12.0	12.2	+1.7	7.42	5.23	-29.5

Notes: The table reports changes in life cycle outcomes under the counterfactual experiment with subsidy with an asset test. Women with assets less than 300% of the federal poverty guideline are given a subsidy capped at $6,100. Baseline results are averages with estimated parameters and observed private school fee in the data. Results for log ability, assets and mean wages are calculated for period 25 (terminal period). Results for private schooling, hours with child and hours worked are calculated by averaging over all time periods.

Table A.8: Subsidizing Different Education Groups

(a) 25% Subsidy to High School Dropouts

	% Change		
	Full Sample	New Entrants	Incumbents
Private School Enrollment	+2.70		
Log Ability	+1.78	+287	0.00
Hours Worked (cond. on working)	+0.54	+113	-0.20
Terminal Assets	+3.87	+116	+0.33
Mean Wages	-0.8	+19.6	-0.03

(b) 25% Subsidy to High School Graduates

	% Change		
	Full Sample	New Entrants	Incumbents
Private School Enrollment	+4.82		
Log Ability	+3.47	+242	0.00
Hours Worked (cond. on working)	+0.86	+97.1	-0.35
Terminal Assets	+4.43	+32.2	+0.61
Mean Wages	+2.36	+18.4	0.00

(c) 25% Subsidy to Women with Some College or More

	% Change		
	Full Sample	New Entrants	Incumbents
Private School Enrollment	+1.04		
Log Ability	+0.003	+1.11	0.00
Hours Worked (cond. on working)	-0.002	+12.5	0.00
Terminal Assets	-0.01	+0.85	-0.02
Mean Wages	0.00	+0.01	0.00

Notes: The table reports changes in life cycle outcomes under the counterfactual experiment with subsidy for different education groups. Panel (a) reports results for the counterfactual in which a 25% subsidy is given to high school dropouts. Panel (b) reports results for the counterfactual in which a 25% subsidy is given to high school graduates. Finally, panel (c) reports results for the counterfactual in which a 25% subsidy is given to women with some college or more. Counterfactual results are compared to the baseline with no subsidy. Results for log ability, assets and mean wages are calculated for period 25 (terminal period). Results for private schooling, hours with child and hours worked are calculated by averaging over all time periods.

Table A.9: School Enrollment by Education and Household Income

(a) Mother's Education

	HSD	HS	College	> College
Public	94.3	85.3	77.5	54.9
Private	5.7	14.7	22.5	45.1

(b) Household Income

	Quantile 1	Quantile 2	Quantile 3	Quantile 4
Public	88.9	82.9	77.4	62.6
Private	11.1	17.1	22.6	37.4

Table A.10: Hours over the life cycle: Marginal Effects

	(1)	(2)	(3)	(4)
4-6 Years Before Birth × Private	286.7***	300.1***	201.9***	208.3***
	(23.98)	(42.20)	(47.44)	(47.12)
1-3 Years Before Birth × Private	142.4***	126.5***	92.94***	86.19**
	(26.34)	(32.33)	(35.06)	(34.62)
Child Age 0-2 × Private	53.52*	84.56***	41.52	45.02
	(28.49)	(27.42)	(31.00)	(30.46)
Child Age 3-5 × Private	-112.3***	-59.91**	-91.12***	-90.66***
	(31.66)	(30.36)	(35.13)	(34.52)
Child Age 6-8 × Private	-148.1***	-94.57***	-147.3***	-153.4***
	(35.75)	(34.24)	(36.97)	(36.60)
Child Age 9-11 × Private	-208.7***	-153.5***	-178.0***	-177.7***
	(39.37)	(37.71)	(40.70)	(40.09)
Demographic Controls	N	Y	Y	Y
Education Controls	N	N	Y	Y
Non-labor Income Controls	N	N	Y	Y
State Fixed Effects	N	N	N	Y
Obs.	59712	50091	32610	32409

Notes: *, **, *** denote p-value < 0.10, 0.05, and 0.01, respectively. Standard errors are given in parentheses. The table reports the average effect of choosing private school on mother's annual hours over different periods of the mother's life cycle. Demographic controls include dummies for respondent's age at first birth, race and marital status, and controls for respondent's religion and number of children.

Table A.11: Employment over the life cycle: Marginal Effects

	(1)	(2)	(3)	(4)
4-6 Years Before Birth × Private	0.08***	0.13***	0.05***	0.05***
	(0.02)	(0.02)	(0.01)	(0.01)
1-3 Years Before Birth × Private	0.04***	0.04***	0.01	0.01
	(0.01)	(0.02)	(0.01)	(0.01)
Child Age 0-2 × Private	0.03*	0.03**	0.00	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Child Age 3-5 × Private	-0.04**	-0.03*	-0.04***	-0.04***
	(0.02)	(0.02)	(0.01)	(0.01)
Child Age 6-8 × Private	-0.08***	-0.07***	-0.10***	-0.09***
	(0.02)	(0.02)	(0.01)	(0.01)
Child Age 9-11 × Private	-0.07***	-0.06***	-0.08***	-0.06***
	(0.02)	(0.02)	(0.01)	(0.01)
Demographic Controls	N	Y	Y	Y
Education Controls	N	N	Y	Y
Non-labor Income Controls	N	N	Y	Y
State Fixed Effects	N	N	N	Y
Obs.	59712	50091	32610	32394

Notes: *, **, *** denote p-value < 0.10, 0.05, and 0.01, respectively. Standard errors are given in parentheses. The table reports the average effect of choosing private school on employment decision over different periods of the mother's life cycle. The dependent variable is a dummy for whether the female was employed during the last year. If the female reports working for 6 weeks or less in the past calendar year, I code her as being unemployed. Demographic controls include dummies for respondent's age at first birth, race and marital status, and controls for respondent's religion and number of children.

Table A.12: Probability of Having Savings over the life cycle: Marginal Effects

	(1)	(2)	(3)	(4)
4-6 Years Before Birth × Private	0.16***	0.14***	0.09***	0.08***
	(0.01)	(0.02)	(0.03)	(0.03)
1-3 Years Before Birth × Private	0.18***	0.11***	0.04*	0.03
	(0.01)	(0.01)	(0.02)	(0.02)
Child Age 0-2 × Private	0.19***	0.10***	0.02	0.02
	(0.01)	(0.01)	(0.02)	(0.02)
Child Age 3-5 × Private	0.18***	0.09***	0.04**	0.04**
	(0.01)	(0.01)	(0.02)	(0.02)
Child Age 6-8 × Private	0.15***	0.05***	0.00	-0.00
	(0.01)	(0.02)	(0.02)	(0.02)
Child Age 9-11 × Private	0.15***	0.06***	0.02	0.02
	(0.01)	(0.02)	(0.02)	(0.02)
Demographic Controls	N	Y	Y	Y
Education Controls	N	N	Y	Y
Non-labor Income Controls	N	N	Y	Y
State Fixed Effects	N	N	N	Y
Obs.	46169	39002	24437	24210

Notes: *, **, *** denote p-value < 0.10, 0.05, and 0.01, respectively. Standard errors are given in parentheses. The table reports the average effect of choosing private school on the probability of having savings over different periods of the mother's life cycle. Demographic controls include dummies for respondent's age at first birth, race and marital status, and controls for respondent's religion and number of children.

Table A.13: Real Assets over the life cycle: Marginal Effects

	(1)	(2)	(3)	(4)
4-6 Years Before Birth × Private	2.20***	0.24	-0.52	-0.78
	(0.42)	(0.88)	(0.89)	(0.90)
1-3 Years Before Birth × Private	2.89***	0.78	0.15	-0.15
	(0.70)	(0.96)	(0.97)	(0.97)
Child Age 0-2 × Private	3.32***	1.35***	0.74	0.45
	(0.47)	(0.50)	(0.50)	(0.48)
Child Age 3-5 × Private	6.65***	4.74***	4.14***	3.98***
	(1.36)	(1.33)	(1.34)	(1.32)
Child Age 6-8 × Private	5.32***	3.36***	2.78**	2.66**
	(1.10)	(1.11)	(1.11)	(1.07)
Child Age 9-11 × Private	7.75***	5.55***	4.86***	4.63***
	(1.73)	(1.73)	(1.71)	(1.69)
Demographic Controls	N	Y	Y	Y
Education Controls	N	N	Y	Y
State Fixed Effects	N	N	N	Y
Obs.	29423	25609	25609	25351

Notes: *, **, *** denote p-value < 0.10, 0.05, and 0.01, respectively. Standard errors are given in parentheses. The table reports the average effect of choosing private school on real assets held by the household over different periods of the mother's life cycle. Demographic controls include dummies for respondent's age at first birth, race and marital status, and controls for respondent's religion and number of children. The dependent variable has been divided by 10,000.

Table A.14: Labor Supply and Savings Response over Child's Life Cycle

	Annual Hours	Real Assets	Have Savings	Employed
4-6 Years Before Birth × Private × Educ × Non-Labor Inc	-0.254	-0.011*	0.004	0.004
	(0.415)	(0.006)	(0.003)	(0.003)
1-3 Years Before Birth × Private × Educ × Non-Labor Inc	-0.0348	0.015	0.002	0.002*
	(0.204)	(0.009)	(0.002)	(0.001)
Child Age 0-2 Years × Private × Educ × Non-Labor Inc	-0.226	0.019*	0.002	0.001*
	(0.171)	(0.010)	(0.002)	(0.000)
Child Age 3-5 Years × Private × Educ × Non-Labor Inc	-0.755***	0.052*	-0.001	-0.001
	(0.247)	(0.027)	(0.001)	(0.001)
Child Age 6-8 Years × Private × Educ × Non-Labor Inc	-0.782**	-0.040	0.002	-0.003***
	(0.363)	(0.039)	(0.002)	(0.001)
Child Age 9-11 Years × Private × Educ × Non-Labor Inc	-0.052	-0.007	-0.001	-0.000
	(0.744)	(0.026)	(0.002)	(0.001)
4-6 Years Before Birth	-565.2***	0.775	-0.310***	-0.070
	(27.68)	(0.915)	(0.076)	(0.072)
1-3 Years Before Birth	-408.0***	1.047	-0.353***	0.320***
	(21.46)	(0.849)	(0.076)	(0.058)
Child Age 0-2 Years	-414.3***	0.973	-0.372***	0.262***
	(19.31)	(0.875)	(0.085)	(0.046)
Child Age 3-5 Years	-280.9***	1.804*	-0.125**	0.384***
	(19.90)	(0.990)	(0.063)	(0.048)
Child Age 6-8 Years	-190.6***	0.192	-0.106*	0.324***
	(21.04)	(1.502)	(0.063)	(0.053)
Child Age 9-11 Years	-95.32***	1.099	-0.114	0.234***
	(31.15)	(1.157)	(0.070)	(0.055)
Years of Schooling	43.32***	-0.157	0.131***	0.088***
	(3.110)	(0.125)	(0.010)	(0.008)
Non-labor Income	-7.994	-0.528	0.084*	-0.006
	(5.003)	(0.349)	(0.049)	(0.010)
Years of Schooling × Non-Labor Inc	-2.642***	0.128***	-0.003	-0.004***
	(0.355)	(0.033)	(0.004)	(0.001)
Educ × Non-Labor Inc × 4-6 Years Before Birth	3.371***	-0.080***	-0.001	0.004***
	(0.270)	(0.020)	(0.002)	(0.001)
Educ × Non-Labor Inc × 1-3 Years Before Birth	3.155***	-0.096***	0.001	0.004***
	(0.216)	(0.021)	(0.002)	(0.000)
Educ × Non-Labor Inc × Child Age 0-2 Years	3.088***	-0.094***	0.003	0.004***
	(0.193)	(0.021)	(0.003)	(0.000)
Educ × Non-Labor Inc × Child Age 3-5 Years	3.003***	-0.091***	-0.001	0.004***
	(0.220)	(0.020)	(0.002)	(0.001)
Educ × Non-Labor Inc × Child Age 6-8 Years	2.789***	-0.018	-0.001	0.005***
	(0.256)	(0.044)	(0.002)	(0.001)
Educ × Non-Labor Inc × Child Age 9-11 Years	1.040	-0.035	0.000	0.001
	(0.660)	(0.032)	(0.002)	(0.001)
Private School	-42.30***	0.706	0.129***	-0.194***
	(16.37)	(0.594)	(0.048)	(0.036)
Demographic Controls	Y	Y	Y	Y
State Fixed Effects	Y	Y	Y	Y
Obs.	32334	18165	24158	32319

Notes: *, **, *** denote p-value < 0.10, 0.05, and 0.01, respectively. Standard errors are given in parentheses. The table reports the average effect of choosing private school over different periods of the mother's life cycle for different education and non-labor income groups. Education is measured in years of schooling and non-labor income has been divided by 1000. The dependent variables are annual hours worked, real assets, a dummy for whether the household has savings in a checking, savings or money market account, and a dummy for whether the respondent is employed. Demographic controls include dummies for respondent's age at first birth, race and marital status, and controls for respondent's religion and number of children.

Table A.15: FIRST STEP ESTIMATES

Parameter	Variable	Estimate	Std. Error
(a) Number of Children Transition			
δ_0^n	Constant	-0.77***	0.07
δ_1^n	Age	-0.09***	0.00
δ_2^n	Black	0.18***	0.03
δ_{32}^n	High School	0.15***	0.04
δ_{33}^n	College	0.20***	0.04
δ_{34}^n	More than College	0.21***	0.05
δ_4^n	Married	1.51***	0.03
(b) Marriage Probabilities			
δ_0^m	Constant	-1.32***	0.09
δ_1^m	Age	-0.05***	0.00
δ_2^m	Black	-0.01	0.04
δ_{32}^m	High School	0.10***	0.05
δ_{33}^m	College	0.09**	0.05
δ_{34}^m	More than College	0.04	0.05
δ_4^m	Child > 6	-0.11**	0.06
(c) Divorce Probabilities			
δ_0^d	Constant	-3.92***	0.12
δ_1^d	Age	0.02***	0.00
δ_2^d	Black	0.19***	0.05
δ_{32}^d	High School	-0.28***	0.06
δ_{33}^d	College	-0.45***	0.06
δ_{34}^d	More than College	-1.06***	0.08
δ_4^d	Child > 6	1.12*	0.07

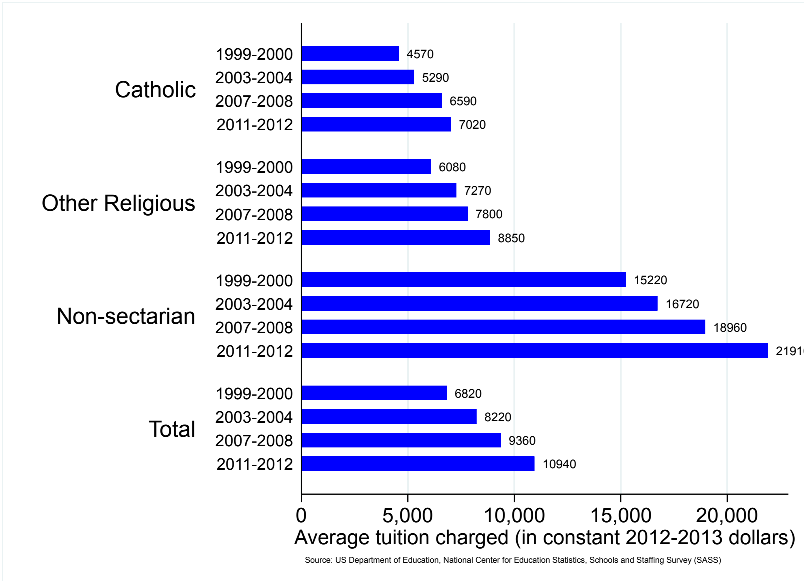
Notes: The table reports the logit estimates from the first step of the estimation, in which the exogenous transition probabilities of marriage, divorce and number of children is calculated using data from NLSY79.
* $p < 0.10$,** $p < 0.05$, ***$p < 0.01$. Standard Errors in parentheses.

Table A.16: Model Fit

Child Age	Pvt School	Pvt/Pub $\ln k$	Exper Avg	Exper Pub	Exper Pvt
Data					
-6			8.392	8.197	8.934
-5			8.634	8.469	9.119
-4			8.840	8.700	9.266
-3			9.008	8.883	9.397
-2			9.134	9.038	9.467
-1			9.265	9.176	9.579
0			9.358	9.292	9.623
1			9.428	9.364	9.686
2			9.472	9.418	9.717
3		1.085	9.537	9.484	9.759
4		1.099	9.576	9.522	9.812
5	0.165	1.125	9.642	9.589	9.850
6	0.184	1.120	9.687	9.637	9.904
7	0.173	1.007	9.759	9.712	9.939
8	0.202	0.981	9.786	9.739	9.984
9	0.188	1.010	9.851	9.807	10.01
10	0.220	1.027	9.878	9.833	10.05
11	0.204	1.078	9.917	9.877	10.06
12	0.229	1.098	9.946	9.905	10.12
13	0.213	1.063	9.981	9.946	10.11
14	0.234	1.075	10.02	9.982	10.17
15	0.214		10.03	10.01	10.13
16	0.211		10.06	10.03	10.19
17	0.191		10.08	10.07	10.16
18	0.179		10.10	10.08	10.17
Model Simulation					
-6			6.384	8.338	8.372
-5			6.384	8.338	8.372
-4			7.509	8.590	8.520
-3			7.707	8.788	8.637
-2			7.841	8.950	8.732
-1			7.942	9.087	8.809
0			8.028	9.206	8.873
1			8.545	9.305	9.009
2			8.760	9.380	9.104
3		0.947	8.893	9.444	9.181
4		0.962	9.010	9.502	9.256
5	0.174	0.976	9.101	9.554	9.324
6	0.302	0.989	9.300	9.645	9.435
7	0.286	1.000	9.349	9.719	9.455
8	0.281	1.007	9.388	9.789	9.473
9	0.284	1.009	9.422	9.852	9.490
10	0.273	1.010	9.452	9.909	9.506
11	0.270	1.016	9.481	9.960	9.522
12	0.259	1.016	9.508	10.01	9.539
13	0.254	1.018	9.534	10.05	9.557
14	0.250	1.298	9.561	10.09	9.575
15	0.245		9.587	10.13	9.593
16	0.240		9.612	10.17	9.612
17	0.238		9.638	10.21	9.632
18	0.228		9.688	10.28	9.675

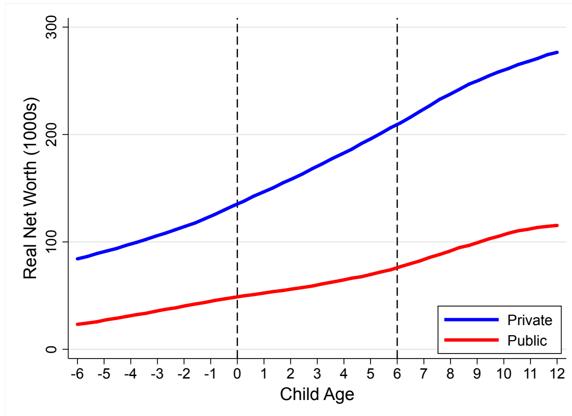
Notes: The table reports goodness of fit for the method of moment estimation.

A.6 Figures



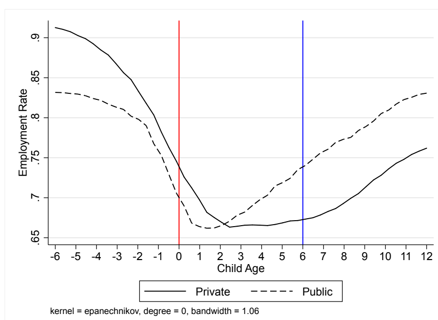
The Figure plots average tuition costs for different types of private schools for four different time periods.

Figure A.1: AVERAGE TUITION COSTS OVER TIME

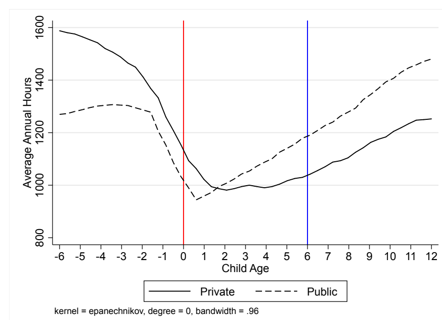


The Figure plots average real net worth for private and public school mothers. The x-axis is child's age, with negative ages denoting years before childbirth.

Figure A.2: Real Net Worth



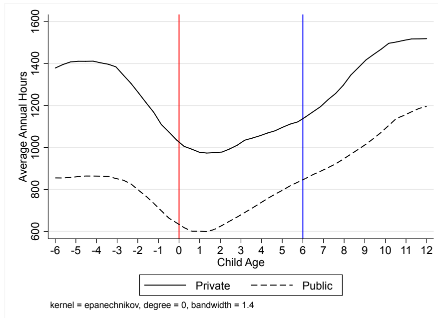
(a) Annual Employment Rate



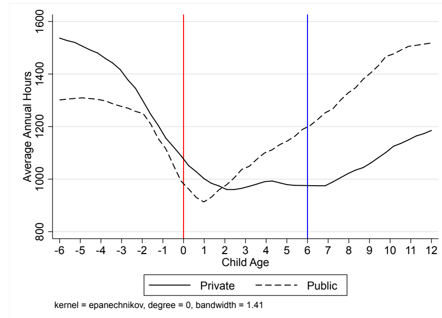
(b) Average Annual Hours

Figure A.3 (a) plots the annual employment rate for private and public school mothers over the child's life cycle, while Figure A.3 (b) plots the average annual hours worked by the two groups of women. The x-axis is child's age, with negative ages denoting years before childbirth.

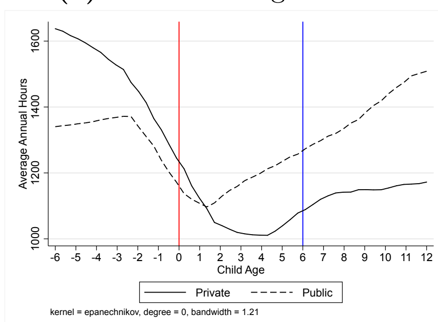
Figure A.3: Labor Supply over the life cycle



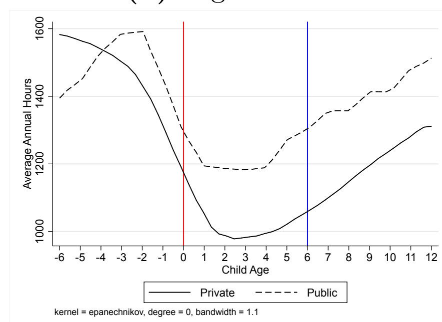
(a) Less than High School



(b) High School



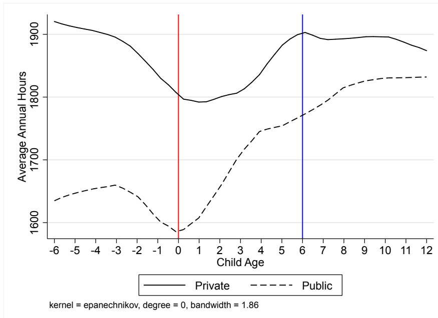
(c) Some College



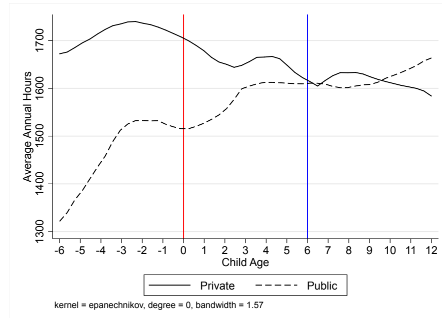
(d) College and More

The Figure plots average annual hours worked by private and public school mothers for four education groups: (1) High school dropouts, (2) high school graduates, (3) some college and (4) college post-graduate degree holders. The x-axis is child's age, with negative ages denoting years before childbirth.

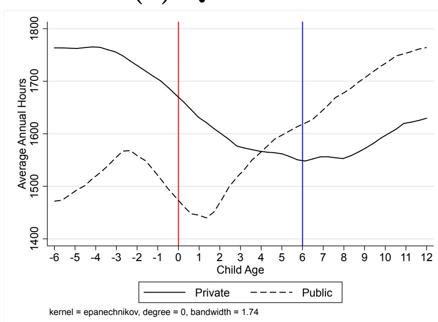
Figure A.4: Annual Hours Worked - Education Groups



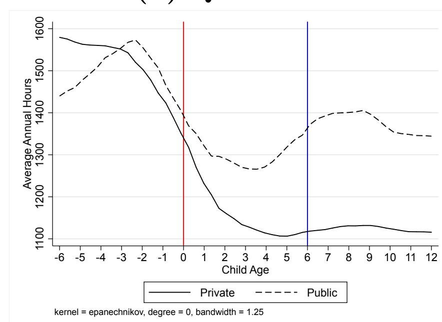
(a) Quantile 1



(b) Quantile 2



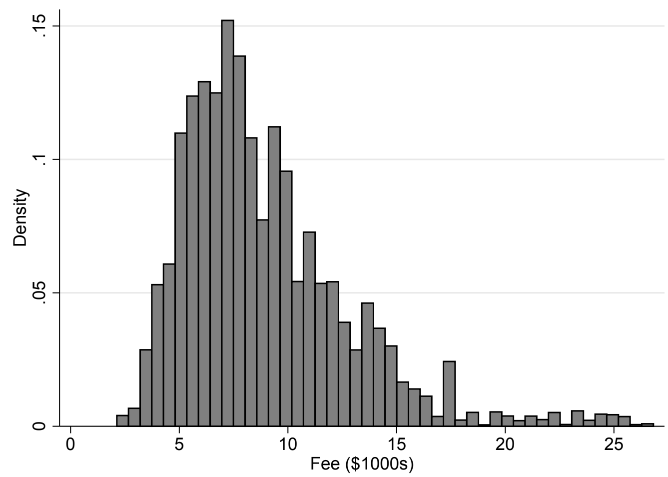
(c) Quantile 3



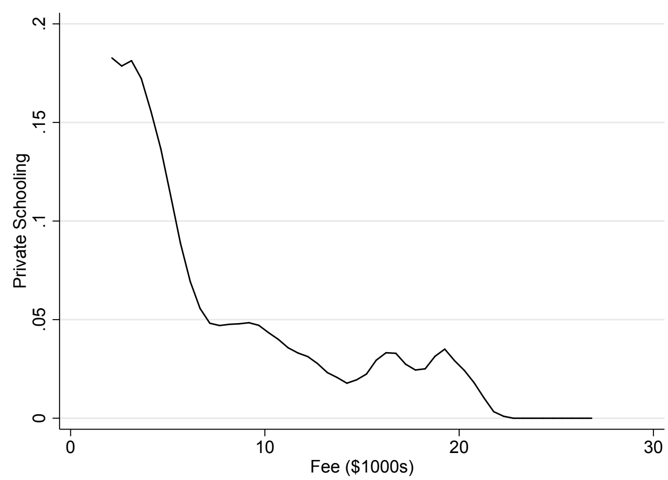
(d) Quantile 4

The Figure plots average annual hours worked by private and public school mothers for non-labor income groups, where non-labor income is defined as family income minus the woman's wage income. The x-axis is child's age, with negative ages denoting years before childbirth.

Figure A.5: Annual Hours Worked - Income Quantiles



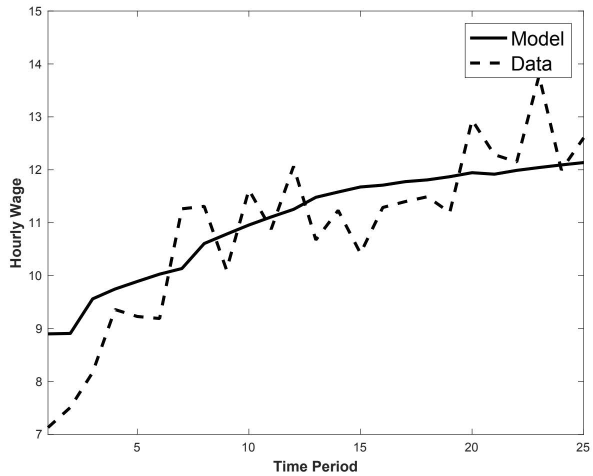
(a) Private School Fee Distribution



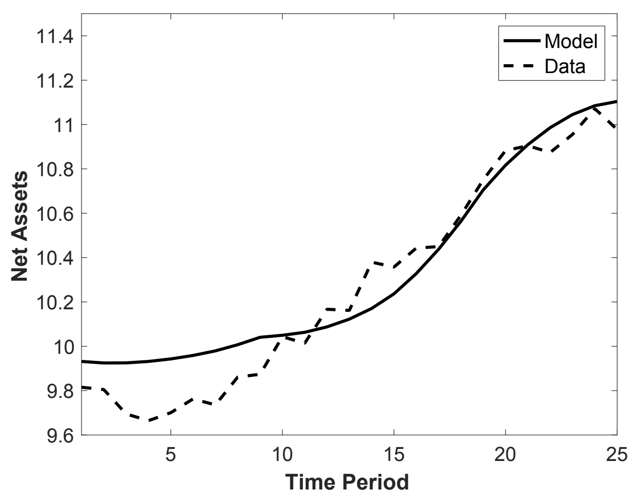
(b) Private School Enrollment and Private School Fee

Figure A.6(a) plots the distribution of state-level private school tuition averages in the sample. Figure A.6 (b) plots the relationship between the probability of sending child to private school fee and private school tuition.

Figure A.6: Distribution Plots



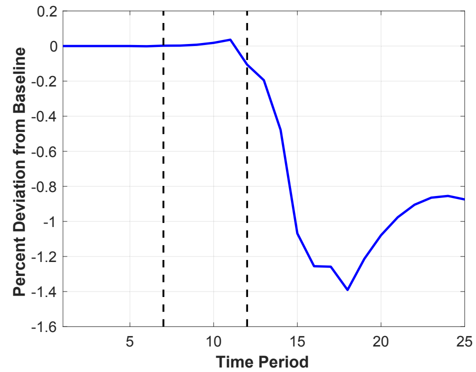
(a) Hourly Wage



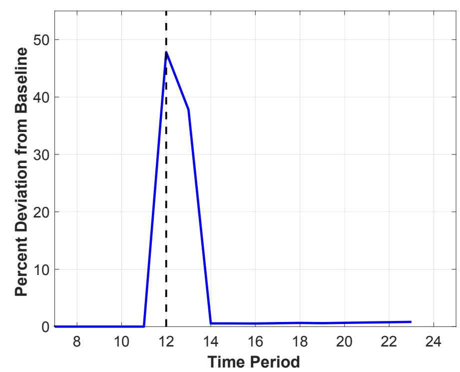
(b) Assets

Figure A.7 (a) shows the model simulation and data hourly wage over the 25 time periods, while Figure A.7 (b) shows the average simulated and data assets over the life cycle.

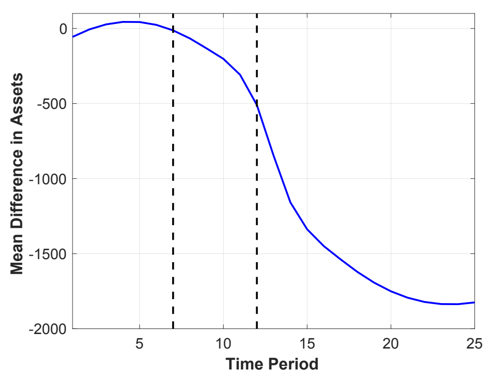
Figure A.7: Goodness of Fit



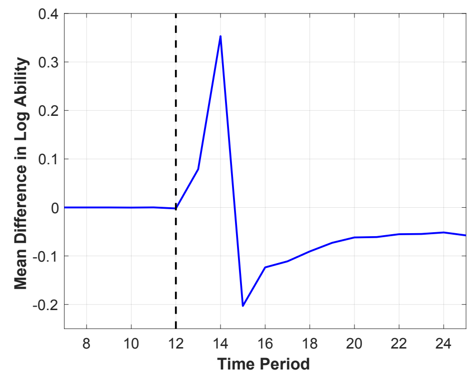
(a) Employment Rate



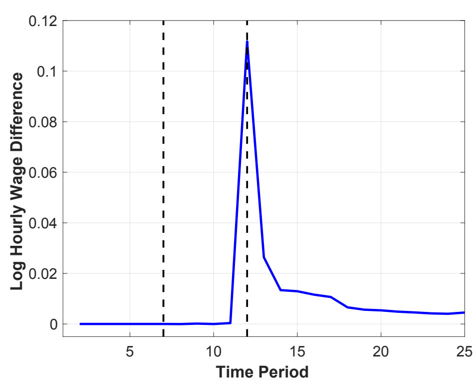
(b) Mother's Time with Child



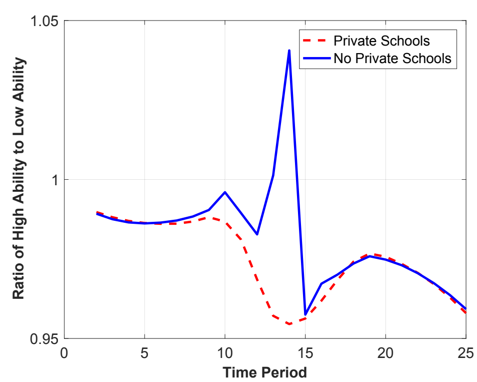
(c) Net Assets



(d) Child Ability



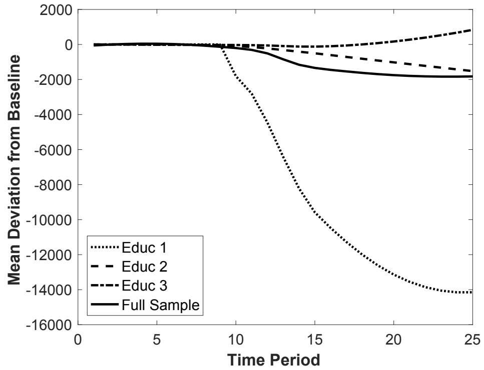
(e) Hourly Wage



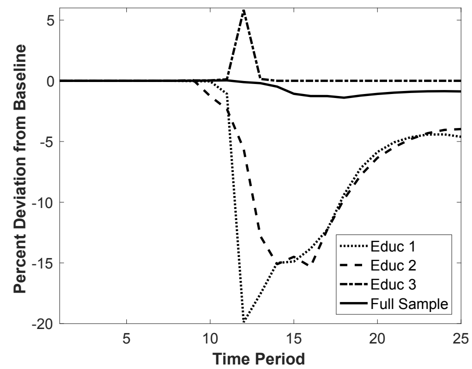
(f) Ratio of High Ability to Low Ability

The different panels display differences in outcomes between a baseline scenario and one where woman don't have the private school option for their child. Figure A.8 (a) shows the percent change in employment rate from baseline, Figure A.8 (b) shows the change in mother's time with the child from baseline, Figure A.8 (c) plots the difference in assets over the life cycle, Figure A.8 (d) plots the difference from baseline in log ability over the life cycle, Figure A.8 (e) plots hourly log wage difference and Figure A.8 (f) plots the ratio of low to high ability women conditional on working for the baseline and counterfactual scenario.

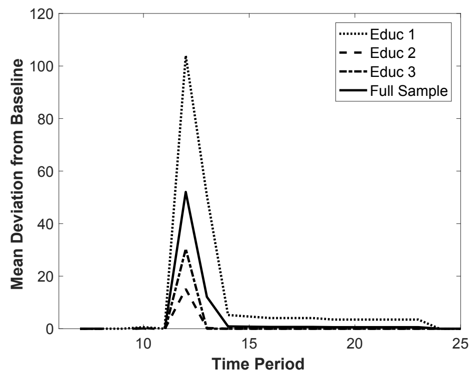
Figure A.8: Shutting Down the Private Schooling Channel



(a) Assets by Education



(b) Employment Rate by Education



(c) Mother's Time with Child by Education

Figure A.9 (a) show the change in assets by education, Figure A.9 (b) show the change in hours worked by education, and Figure A.9 (c) plot the change in mother's time with the child from baseline by education.

Figure A.9: Shutting Down the Private Schooling Channel

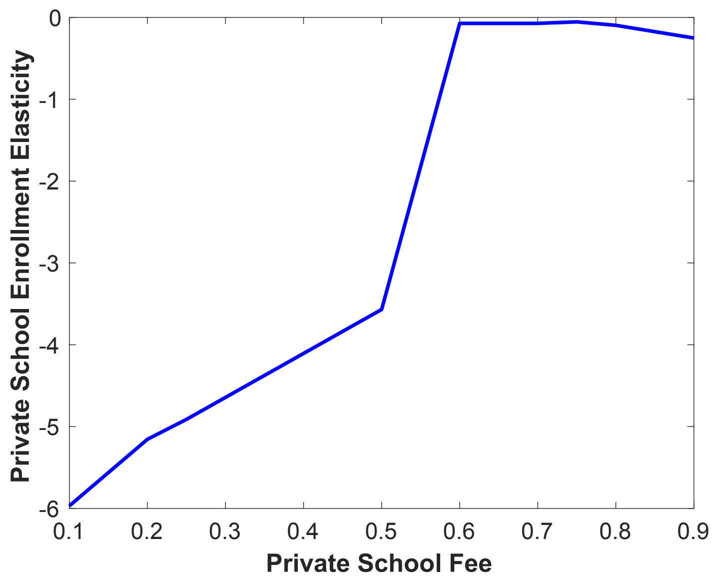


Figure A.10 plots the elasticity of private school enrollment for different levels of fee. The x-axis markers represent the percentage of observed fee at which the elasticity has been calculated.

Figure A.10: Price Elasticity of Private School Enrollment

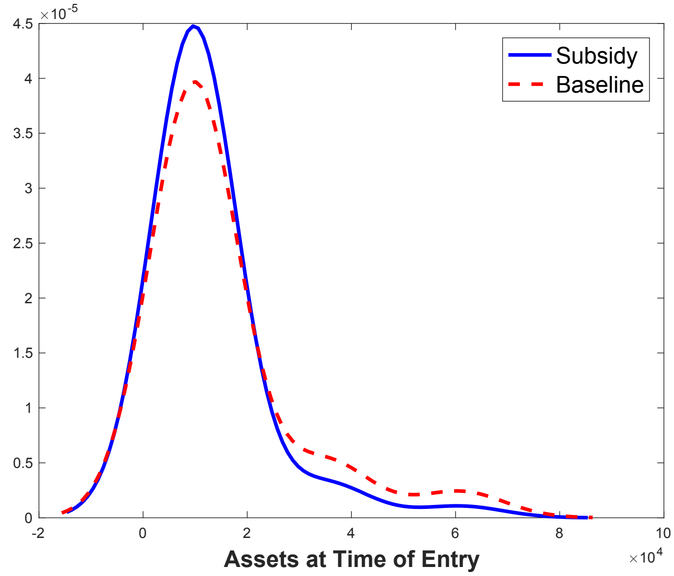
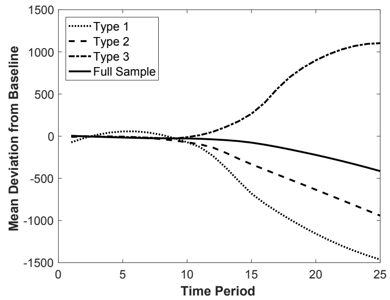
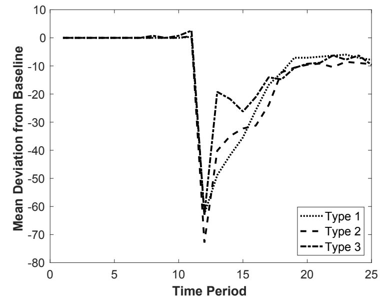


Figure A.11 plots the baseline and counterfactual asset distribution of mothers at the time of child's entry into private schooling.

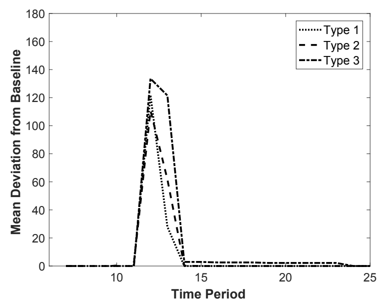
Figure A.11: Asset Distribution at Time of Entry



(a) Assets by Type



(b) Hours Worked by Type



(c) Mother's Time with Child by Type

Figure A.12 (a) show the change in assets by type, Figure A.12 (b) show the change in hours worked by type, and Figure A.12 (c) plot the change in mother's time with the child from baseline by type.

Figure A.12: Shutting Down the Private Schooling Channel

Appendix B

Appendix for Chapter 2

B.1 Tables

Table B.1: Summary Statistics

	Mean	Std. Dev	Min	Max
Private School Enrollment %				
Year 2000	9.03	4.95	0	26
Year 2006	9.32	5.62	0	29
Year 2012	8.90	6.38	0	39
Δ Private School Enrollment %				
2000-2006	0.26	6.18	-22.7	27.2
2006-2012	-0.46	7.52	-27.3	38.9
Local Housing Demand Measures				
Log House Price Index (2000)	0.72	0.07	0.50	1.10
Log House Price Index (2006)	1.07	0.45	0.65	2.80
House Price Growth 2000-2006	0.33	0.34	-0.06	1.25
Housing Supply Growth 2000-2006	0.21	0.36	-0.55	1.99
Housing Demand Shock 2000-2006	0.54	0.57	-0.61	3.08
Magnitude of Structural Break	0.05	0.07	-0.10	0.27
Demographic Controls for Year 2000				
Share of College Graduates	0.58	0.08	0.33	0.76
Share of Females Employed	0.72	0.06	0.33	0.76
Proportion of African Americans	0.23	0.22	0	0.83
Proportion below Poverty Line	0.20	0.09	0	0.75
Number of Children	5718	15917	0	148344
Number of School-going Children	5161	14353	0	137760
Median Household Income	41.0	7.10	24.9	74.3
School Controls for Year 2000				
Number of Public Schools	208	288	27	2184
Student Teacher Ratio in Public Schools	11.4	1.63	7.37	18.3
Current Expenditure Per Pupil in Public Schools	6921	1314	4501	13611
Total Expenditure Per Pupil in Public Schools	8365	1707	5318	17095
Proportion of Free Lunch Students in Public Schools	0.38	0.17	0	0.78
Stat-level Private School Tuition	6114	1947	1834	15879
No. of Obs.	259			

Notes: The table reports summary statistics for percentage of students enrolled in private school in years 2000, 2006 and 2012, and MSA-level averages of demographics and public school quality measures for the year 2000. Private school enrollment in 2012 is top-coded at the 99% value. Median Household Income has been divided by 1000. Housing price growth is the difference in log of HPI in 2006 and log of HPI in 2000. Housing supply growth is the difference in log of new privately owned housing units in 2006 and log of new privately owned housing units in 2000. Housing demand shock is the sum of house price growth and housing supply growth during 2000-2006.

Table B.2: Summary Statistics: Local Labor Market

	Mean	Std. Dev	Min	Max
a) Local Labor Market Controls for Year 2000				
% Employed in Construction	7.33	1.54	3.9	13.3
% Employed in Manufacturing	14.9	7.23	2.00	42.6
% Employed in FIRE	5.89	1.94	2.73	20.7
% Employed in Transportation	4.98	1.39	1.55	13.9
% Employed in Retail Trade	12.3	1.36	8.00	17.9
% Employed in Wholesale Trade	3.45	0.84	1.30	7.60
Inflation-Adjusted Hourly Wage - Males	12.1	3.18	4.55	24.3
Inflation-Adjusted Hourly Wage - Females	10.3	1.96	6.56	20.8
b) 2000-2006 Δ in %				
Male Annual Wage Income	-0.06	0.45	-1.17	1.98
Female Annual Wage Income	-0.05	0.34	-0.66	1.65
Male Labor Force Participation Rate	0.19	17.8	-83.3	58.0
Female Labor Force Participation Rate	-0.15	13.2	-43.3	53.3
Male Employment Rate	-0.01	0.16	-0.65	0.58
Female Employment Rate	-0.04	0.12	-0.44	0.40
Non-Labor Income	-0.03	0.31	-1.41	0.82
c) 2000-2006 Δ in %				
Male Annual Wage Income	-0.21	0.61	-3.57	0.77
Female Annual Wage Income	-0.21	0.50	-3.41	0.62
Male Labor Force Participation Rate	-0.68	18.8	-57.1	80.0
Female Labor Force Participation Rate	-1.30	15.0	-50.0	53.6
Male Employment Rate	-0.06	0.21	-0.80	0.56
Female Employment Rate	-0.05	0.18	-0.94	0.42
Non-Labor Income	0.01	0.42	-2.65	1.84
No. of Obs.	259			

Notes: The table reports summary statistics for measures of local labor market performance. All wages are in 2000 constant dollars. The values for males and females is an average of all males and females respectively who have a child of school going age. Δ wage income and Δ non-labor income are the difference in log values for each year. Non-labor income is defined as total family income minus any wage income from parents of the child. Change in labor force participation has been multiplied by 100.

Table B.3: Relationship between Public School Quality and Housing Demand Shock

Dependent Var. is 2000-2006 Δ in	Log Current Expenditure Per Pupil	Log Total Expenditure Per Pupil	Student -Teacher Ratio	Prop. of Free Lunch Students
Housing Demand Shock 2000-2006	0.04***	0.04**	-1.05**	-0.01
	(0.01)	(0.02)	(0.50)	(0.03)
College Share	0.08	-0.16	9.87***	0.51*
	(0.27)	(0.28)	(3.66)	(0.28)
Share of Females Employed	-0.01	0.20	-17.70*	-0.30
	(0.38)	(0.37)	(9.25)	(0.35)
Proportion of African-American	0.06	0.14	-2.69*	0.00
	(0.08)	(0.09)	(1.37)	(0.08)
Proportion below Poverty Line	0.19	-0.02	3.59	0.34**
	(0.25)	(0.31)	(4.43)	(0.17)
Log School-Going Children	-0.01	-0.00	0.28	-0.02***
	(0.01)	(0.01)	(0.20)	(0.01)
Female Hourly Wage	-0.00	-0.01	-0.37	0.01
	(0.01)	(0.01)	(0.26)	(0.01)
Male Hourly Wage	-0.00	-0.00	0.06	0.01
	(0.00)	(0.00)	(0.13)	(0.01)
Median Household Income	0.00*	0.00	0.08	-0.00
	(0.00)	(0.00)	(0.07)	(0.00)
Industry Controls	N	N	N	Y
No. of Obs.	264	264	218	264

Notes: The table reports OLS estimates of the effect of the housing demand shock between 2000-2006 in an MSA, measured by the change in house prices and change in supply of housing, affects current expenditure per pupil, total expenditure per pupil, student-teacher ratio and proportion of free lunch students in public schools in the MSA. Industry controls include the percentage of individuals employed in construction, manufacturing, retail trade, wholesale trade, transportation and FIRE industries in an MSA in 2000.
* $p < 0.10$,** $p < 0.05$, ***$p < 0.01$. Standard Errors in parentheses.

Table B.4: PRIVATE SCHOOLING AND HOUSING DEMAND SHOCK

	(1)	(2)	(3)	(4)
Housing Demand Shock 2000-2006	-0.00	0.01	0.01	0.00
	(0.00)	(0.01)	(0.01)	(0.01)
College Share		-0.14***	-0.13***	-0.10**
		(0.04)	(0.04)	(0.05)
Share of Females Employed		0.04	0.02	0.11
		(0.07)	(0.08)	(0.07)
Proportion of African-American		0.03	0.03	0.03*
		(0.02)	(0.02)	(0.02)
Proportion below Poverty Line		0.03	0.03	0.03
		(0.07)	(0.07)	(0.07)
Log Median Household Income		0.02	0.02	0.05**
		(0.03)	(0.03)	(0.02)
Log Private School Fee		-0.01	-0.01	-0.02
		(0.01)	(0.01)	(0.02)
Log School-going Children			-0.00	0.00
			(0.00)	(0.00)
Female Log Hourly Wage				-0.01
				(0.03)
Male Log Hourly Wage				0.01
				(0.02)
Student-Teacher Ratio				0.00
				(0.00)
Total Public Schools				-0.00**
				(0.00)
Log Current Expenditure Per Pupil				0.01
				(0.02)
Prop. of Free Lunch Students				0.02
				(0.02)
Industry Controls	N	N	N	Y
No. of Obs.	259	259	259	259

Notes: The table reports OLS estimates of the effect of the housing demand shock between 2000-2006 in an MSA, measured by the change in house prices and change in supply of housing, on private school enrollment in the MSA. Industry controls include the percentage of individuals employed in construction, manufacturing, retail trade, wholesale trade, transportation and FIRE industries in an MSA in 2000.
* $p < 0.10$,** $p < 0.05$, ***$p < 0.01$. Standard Errors in parentheses.

Table B.5: CORRELATION BETWEEN STRUCTURAL BREAK AND HOUSING DEMAND SHOCK

	Structural Break 2000-2006	**Housing Demand Shock 2000-2006**	**Housing Demand Shock 2006-2012**
Structural Break 2000-2006	1.00		
Housing Demand Shock 2000-2006	0.70	1.00	
Housing Demand Shock 2006-2012	-0.60	-0.65	1.00

Table B.6: FIRST STAGE FOR HOUSING DEMAND CHANGE

Dependent Variable is 2000-2006 Change in	Housing Demand	House Prices	Housing Permits
Magnitude of Structural Break in House Prices	5.08***	3.87***	1.21***
	(0.76)	(0.53)	(0.44)
F-statistic	68.83	71.85	19.92
MSA-level Controls	Y	Y	Y
No. of Obs.	259	259	259

Notes: The table reports results for the first stage for housing demand change. Columns (1), (2) and (3) show how the magnitude of structural break in house prices affects change in housing demand, house prices and no. of housing permits granted between 2000-2006. MSA-level controls include the share of college educated individuals, shares of females employed, proportion of African-Americans, proportion of individuals living below the poverty line and log of the population of school-going children in the MSA in 2000.
* $p < 0.10$,** $p < 0.05$, ***$p < 0.01$. Standard Errors in parentheses.

Table B.7: PUBLIC SCHOOL QUALITY AND STRUCTURAL BREAK IN HOUSE PRICES

Dependent Var. is 2000-2006 Δ in	Log Current Expenditure Per Pupil	Log Total Expenditure Per Pupil	Student -Teacher Ratio	Prop. of Free Lunch Students
Structural Break in House Prices	0.10**	0.10**	-0.09	0.04
	(0.04)	(0.05)	(0.69)	(0.06)
College Share	0.14	-0.11	10.57***	0.55**
	(0.28)	(0.30)	(3.62)	(0.26)
Share of Females Employed	0.25	0.45	-13.45	-0.08
	(0.35)	(0.35)	(9.76)	(0.35)
Proportion of African-American	0.12	0.18	-1.85	0.05
	(0.10)	(0.11)	(1.50)	(0.06)
Proportion below Poverty Line	0.25	0.04	4.50	0.39**
	(0.26)	(0.32)	(4.33)	(0.17)
Log School-Going Children	-0.02	-0.02	0.08	-0.04**
	(0.02)	(0.02)	(0.23)	(0.02)
Female Hourly Wage	-0.01	-0.01*	-0.42	0.00
	(0.01)	(0.01)	(0.26)	(0.01)
Male Hourly Wage	-0.01	-0.00	0.02	0.01
	(0.00)	(0.00)	(0.13)	(0.01)
Median Household Income	0.01**	0.00	0.09	0.00
	(0.00)	(0.00)	(0.07)	(0.00)
Industry Controls	N	N	N	Y
No. of Obs.	266	266	220	266

Notes: The table reports IV estimates of the effect of the housing demand shock between 2000-2006 in an MSA between 2000 and 2006, instrumented by the magnitude of the structural break in house prices in an MSA, affects current expenditure per pupil, total expenditure per pupil, student-teacher ratio and proportion of free lunch students in public schools in the MSA. Industry controls include the percentage of individuals employed in construction, manufacturing, retail trade, wholesale trade, transportation and FIRE industries in an MSA in 2000.
* $p < 0.10$,** $p < 0.05$, ***$p < 0.01$. Standard Errors in parentheses.

Table B.8: Private Schooling and Structural Break in House Prices

	(1)	(2)	(3)	(4)
Structural Break in House Prices 2000-2006	0.01	0.03**	0.02**	0.03**
	(0.01)	(0.01)	(0.01)	(0.01)
College Share		-0.14***	-0.13***	-0.07
		(0.04)	(0.04)	(0.05)
Share of Females Employed		0.19*	0.12	0.20*
		(0.10)	(0.10)	(0.10)
Proportion of African-American		0.05*	0.05*	0.05**
		(0.02)	(0.02)	(0.02)
Proportion below Poverty Line		0.05	0.04	0.03
		(0.07)	(0.07)	(0.07)
Log Private School Fee		-0.02	-0.02	-0.03
		(0.02)	(0.02)	(0.02)
Log Median Household Income		0.02	0.03	0.06***
		(0.03)	(0.03)	(0.02)
Log School-going Children			-0.00	0.00
			(0.00)	(0.00)
Female Log Hourly Wage				-0.03
				(0.03)
Male Log Hourly Wage				-0.00
				(0.03)
Student-Teacher Ratio				-0.00
				(0.00)
Total Public Schools				-0.00**
				(0.00)
Log Current Expenditure Per Pupil				0.01
				(0.02)
Prop. of Free Lunch Students				0.01
				(0.02)
Industry Controls	N	N	N	Y
No. of Obs.	259	259	259	259

Notes: The table reports IV estimates of the effect of the housing demand shock between 2000-2006 in an MSA, instrumented by the magnitude of the structural break in house prices in an MSA, on private school enrollment in the MSA. Industry controls include the percentage of individuals employed in construction, manufacturing, retail trade, wholesale trade, transportation and FIRE industries in an MSA in 2000.
$*$ $p < 0.10$,** $p < 0.05$, ***$p < 0.01$. Standard Errors in parentheses.

Table B.9: PRIVATE SCHOOL ENROLLMENT DURING THE BUST AND FULL CYCLE

Dependent Var. is Δ in Private School Enrollment during	**2000-2006**	**2000-2012**
Structural Break in House Prices 2000-2006	-0.03**	0.00
	(0.01)	(0.01)
College Share	0.17***	0.10*
	(0.06)	(0.06)
Share of Females Employed	-0.20**	-0.01
	(0.08)	(0.07)
Proportion of African-American	-0.01	0.04***
	(0.02)	(0.01)
Proportion below Poverty Line	-0.08*	-0.05
	(0.05)	(0.06)
Log Private School Fee	0.04***	0.00
	(0.01)	(0.01)
Log Median Household Income	-0.07***	-0.01
	(0.02)	(0.02)
Industry Controls	Y	Y
Local Labor Market Controls	Y	Y
No. of Obs.	259	259

Notes: The table reports results for the effect of the housing demand shock during the 2000-2006, instrumented by the magnitude of structural break in house prices in 2000-2006, on private school enrollment during the bust period 2006-2012. Column (1) regression is weighted by the population of children of school-going age in an MSA in 2006 while column (2) regression is weighted by the population of children of school-going age in an MSA in 2000. MSA-level controls include the share of college educated individuals, shares of females employed, proportion of African-Americans, proportion of individuals living below the poverty line, log of median household income and log of the population of school-going children in the MSA in 2000. Public school controls include the student-teacher ratio, proportion of free lunch students and log of current expenditure per student in public schools in the MSA in 2000. Industry controls include the percentage of individuals employed in construction, manufacturing, retail trade, wholesale trade, transportation and FIRE industries in an MSA in 2000 and local labor market controls include average log hourly wage for males and females.
* $p < 0.10$,** $p < 0.05$, ***$p < 0.01$. Standard Errors in parentheses.

Table B.10: Decomposing the Effect of Housing Demand Shock

2000-2006 Δ in Private School Enrollment	(1)	(2)	(3)
Housing Demand Shock 2000-2006	0.01	0.03*	0.03*
	(0.02)	(0.02)	(0.02)
Housing Demand × Elasticity	0.00	-0.01	-0.01
	(0.01)	(0.01)	(0.01)
Elasticity	0.00	0.00	-0.00
	(0.01)	(0.01)	(0.01)
Demographic Controls	N	Y	Y
Public School Controls	N	N	Y
Local Labor Market Controls	N	N	Y
No. of Obs.	226	226	226

Notes: The table reports IV estimates decomposing the housing demand shock into changes in housing prices and changes in housing supply. The variable elasticity is the housing supply elasticity estimates from Saiz (2010). The interaction term between housing demand shock and elasticity captures whether the local housing demand had differential effects across MSAs with different housing supply elasticities. Demographic controls include the share of college educated individuals, shares of females employed, proportion of African-Americans, proportion of individuals living below the poverty line, median household income and log of the population of school-going children in the MSA in 2000, while public school controls include the student-teacher ratio, proportion of free lunch students and log of current expenditure per student in public schools in the MSA in 2000. Industry controls include the percentage of individuals employed in construction, manufacturing, retail trade, wholesale trade, transportation and FIRE industries in an MSA in 2000, and local labor market controls include average hourly wage for males and females.
* $p < 0.10$,** $p < 0.05$, ***$p < 0.01$. Standard Errors in parentheses.

Table B.11: Labor Market Effects for Fathers During Boom

Dependent Var. is 2000-2006 Δ in	**LFP**	**Employment Rate**	**Annual Wage Income**	**Non-labor Income**
Structural Break in House Prices 2000-2006	0.05**	0.02	0.22**	0.23***
	(0.02)	(0.03)	(0.10)	(0.04)
College Share	-0.12	0.15*	0.13	0.04
	(0.13)	(0.08)	(0.40)	(0.29)
Share of Females Employed	-0.15	0.25	0.36	1.12**
	(0.20)	(0.23)	(0.61)	(0.48)
Proportion of African-American	0.06**	-0.07***	0.02	0.01
	(0.03)	(0.02)	(0.10)	(0.08)
Proportion below Poverty Line	0.27**	0.27***	1.34***	1.23***
	(0.11)	(0.10)	(0.42)	(0.26)
Log Median Household Income	0.14**	0.02	0.36*	0.30***
	(0.06)	(0.04)	(0.20)	(0.10)
Industry Controls	Y	Y	Y	Y
Public School Controls	Y	Y	Y	Y
No. of Obs.	256	256	255	259

Notes: The table reports results for the effect of the housing demand shock during the 2000-2006, instrumented by the magnitude of structural break in house prices in 2000-2006, on labor market outcomes of fathers of children of school-going age during 2000-2006. Industry controls include the percentage of individuals employed in construction, manufacturing, retail trade, wholesale trade, transportation and FIRE industries in an MSA in 2000. Public school controls include the student-teacher ratio, proportion of free lunch students and log of current expenditure per student in public schools in the MSA in 2000. Non-labor income is defined as family income minus wage income earned by any parent.

* $p < 0.10$,** $p < 0.05$, ***$p < 0.01$. Standard Errors in parentheses.

Table B.12: Labor Market Effects for Mothers during Boom

Dependent Var. is 2000-2006 Δ in	**LFP**	**Employment Rate**	**Annual Wage Income**
Structural Break in House Prices 2000-2006	0.01	0.02*	0.03
	(0.02)	(0.01)	(0.04)
College Share	0.07	-0.18**	-0.44*
	(0.10)	(0.09)	(0.25)
Share of Females Employed	-0.23	0.08	-0.25
	(0.18)	(0.18)	(0.54)
Proportion of African-American	0.02	-0.03	-0.09*
	(0.02)	(0.03)	(0.05)
Proportion below Poverty Line	-0.04	0.06	0.22
	(0.11)	(0.08)	(0.26)
Log Median Household Income	0.04	0.03	0.22*
	(0.04)	(0.04)	(0.12)
Industry Controls	Y	Y	Y
Public School Controls	Y	Y	Y
No. of Obs.	259	259	259

Notes: The table reports results for the effect of the housing demand shock during the 2000-2006, instrumented by the magnitude of structural break in house prices in 2000-2006, on labor market outcomes of mothers of children of school-going age during 2000-2006. Industry controls include the percentage of individuals employed in construction, manufacturing, retail trade, wholesale trade, transportation and FIRE industries in an MSA in 2000. Public school controls include the student-teacher ratio, proportion of free lunch students and log of current expenditure per student in public schools in the MSA in 2000.

* $p < 0.10$,** $p < 0.05$, ***$p < 0.01$. Standard Errors in parentheses.

Table B.13: Labor Market Effects for Fathers During Bust

Dependent Var. is 2000-2006 Δ in	**LFP**	**Employment Rate**	**Annual Wage Income**	**Non-labor Income**
Structural Break in House Prices 2000-2006	-0.07***	-0.01	-0.25***	-0.20***
	(0.02)	(0.02)	(0.08)	(0.06)
College Share	0.02	0.24	0.06	0.17
	(0.20)	(0.16)	(0.58)	(0.38)
Share of Females Employed	-0.11	-0.09	0.04	-0.00
	(0.27)	(0.34)	(0.96)	(0.40)
Proportion of African-American	-0.08*	0.05	-0.13	0.07
	(0.05)	(0.07)	(0.18)	(0.08)
Proportion below Poverty Line	0.09	0.38	0.82	-0.38
	(0.15)	(0.24)	(0.59)	(0.27)
Log Median Household Income	0.02	-0.06	0.39*	-0.35***
	(0.05)	(0.07)	(0.21)	(0.12)
Industry Controls	Y	Y	Y	Y
Public School Controls	Y	Y	Y	Y
No. of Obs.	256	256	255	259

Notes: The table reports results for the effect of the housing demand shock during the 2000-2006, instrumented by the magnitude of structural break in house prices in 2000-2006, on labor market outcomes of fathers of children of school-going age during 2000-2006. All regressions are weighted by the population of children of school-going age in an MSA in 2006. Industry controls include the percentage of individuals employed in construction, manufacturing, retail trade, wholesale trade, transportation and FIRE industries in an MSA in 2000. Public school controls include the student-teacher ratio, proportion of free lunch students and log of current expenditure per student in public schools in the MSA in 2000. Non-labor income is defined as family income minus wage income earned by any parent.

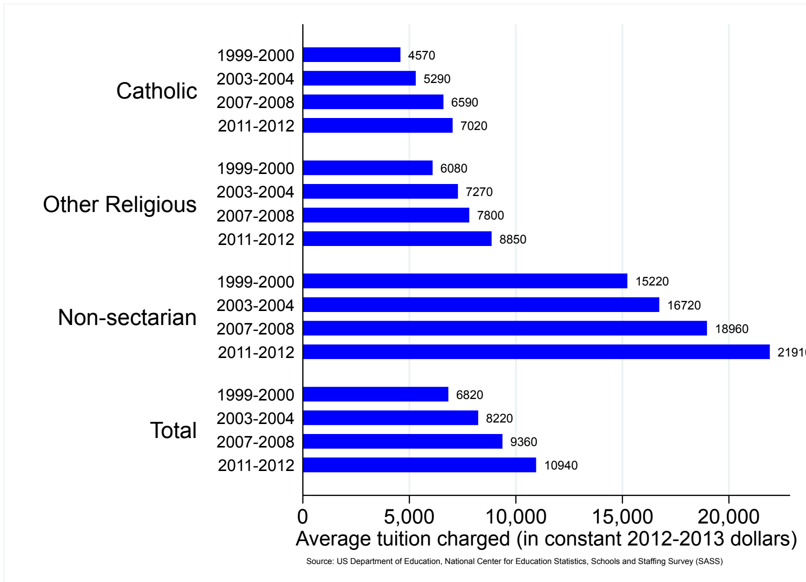
* $p < 0.10$,** $p < 0.05$, ***$p < 0.01$. Standard Errors in parentheses.

Table B.14: Labor Market Effects for Mothers during Bust

Dependent Var. is 2000-2006 Δ in	**LFP**	**Employment Rate**	**Annual Wage Income**
Structural Break in House Prices 2000-2006	-0.03***	-0.08***	-0.12**
	(0.01)	(0.01)	(0.05)
College Share	-0.05	0.23*	0.65
	(0.08)	(0.12)	(0.41)
Share of Females Employed	-0.27*	0.04	-0.23
	(0.16)	(0.23)	(0.64)
Proportion of African-American	-0.01	-0.01	-0.01
	(0.02)	(0.03)	(0.08)
Proportion below Poverty Line	0.00	0.02	0.63
	(0.12)	(0.13)	(0.49)
Log Median Household Income	0.01	-0.02	-0.15
	(0.03)	(0.04)	(0.16)
Industry Controls	Y	Y	Y
Public School Controls	Y	Y	Y
No. of Obs.	259	259	259

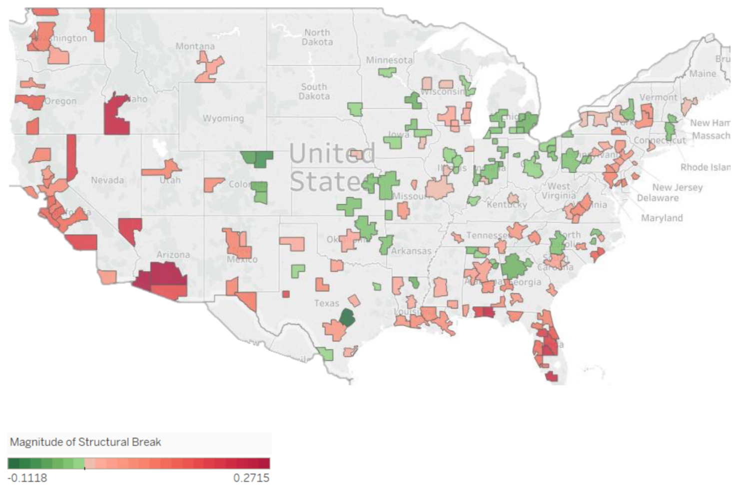
Notes: The table reports results for the effect of the housing demand shock during the 2000-2006, instrumented by the magnitude of structural break in house prices in 2000-2006, on labor market outcomes of mothers of children of school-going age during 2000-2006. All regressions are weighted by the population of school-going children in an MSA in 2006. Industry controls include the percentage of individuals employed in construction, manufacturing, retail trade, wholesale trade, transportation and FIRE industries in an MSA in 2000. Public school controls include the student-teacher ratio, proportion of free lunch students and log of current expenditure per student in public schools in the MSA in 2000.
* $p < 0.10$, ** $p < 0.05$, $^{***}p < 0.01$. Standard Errors in parentheses.

B.2 Figures



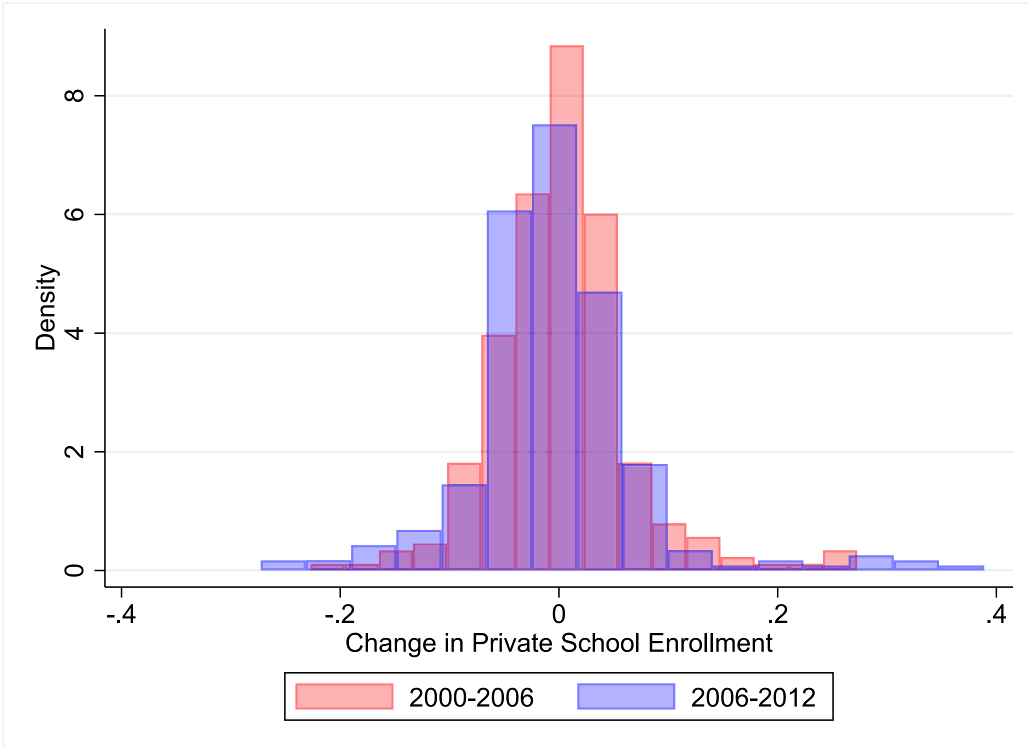
The Figure plots average tuition costs for different types of private schools for four different time periods.

Figure B.1: Average Tuition Costs over Time



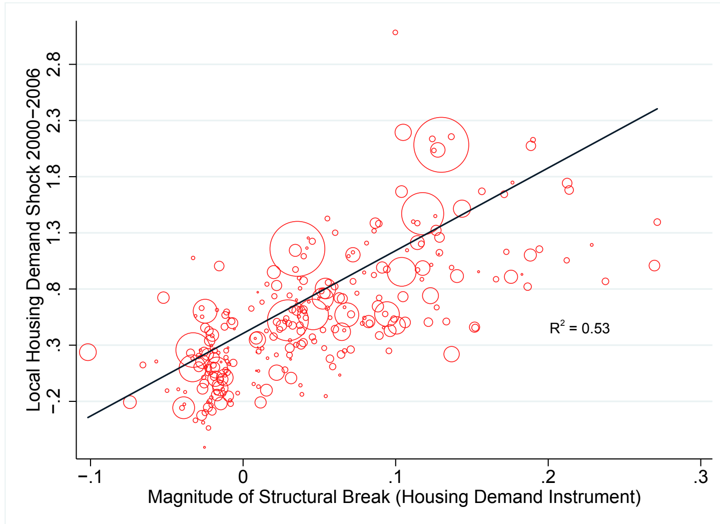
The Figure maps the magnitude of structural break in house prices across metro areas in the US. Red areas experienced the highest change in house prices while lighter shades experienced smaller deviations from a linear trend in house prices.

Figure B.2: Magnitude of Structural Break across MSAs

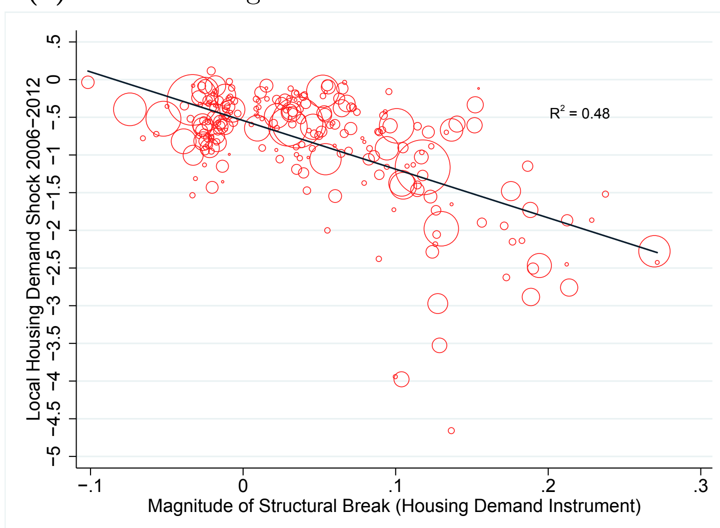


The red histogram shows the distribution of the change in private school enrollment between 2000-2006, while the blue histogram shows the distribution of the change in private school enrollment between 2006-2012.

Figure B.3: Change in Private School Enrollment Distribution



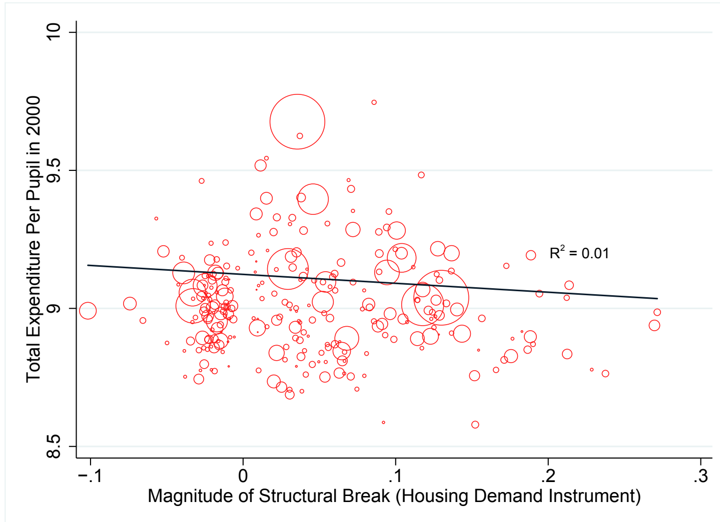
(a) Local Housing Demand Shock between 2000-2006



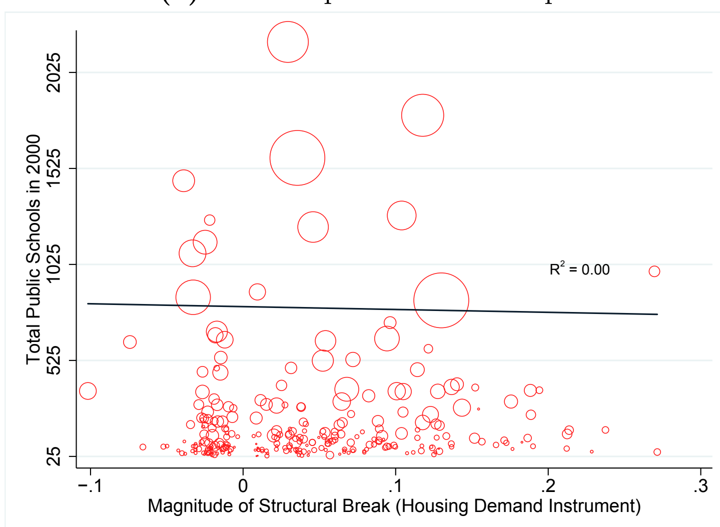
(b) Local Housing Demand Shock between 2006-2012

The Figure plots the relationship between the local housing demand shock between 2000-2006 and 2006-2012, and the magnitude of the estimated structural breaks.

Figure B.4: Relationship between Housing Demand Shock and Magnitude of Structural Break



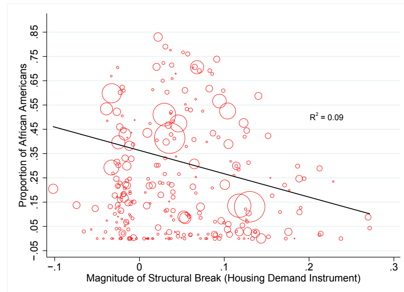
(a) Total Expenditure Per Pupil



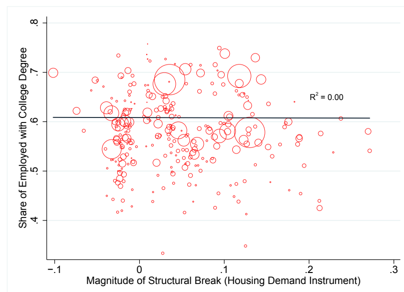
(b) Total Number of Public Schools

The Figure plots the relationship between the instrument variable - magnitude of structural break in housing prices - and public school supply in the baseline year 2000.

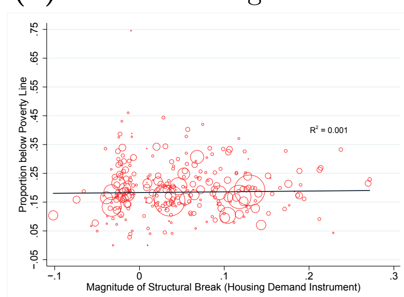
Figure B.5: Relationship between Public School Quality in 2000 and Structural Break



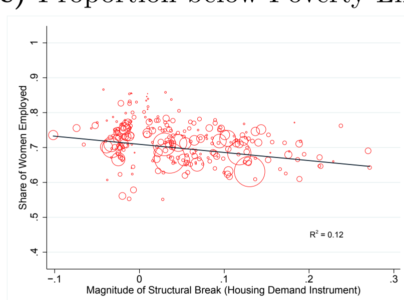
(a) Proportion of African-Americans



(b) Share of College Educated



(c) Proportion below Poverty Line



(d) Share of Employed Females

The Figure plots the relationship between the instrument variable - magnitude of structural break in housing prices - and MSA-level demographics in the baseline year 2000.

Figure B.6: Relationship between Demographics in 2000 and Structural Break

Appendix C

Appendix for Chapter 3

C.1 Theoretical Model

Let drug $d's$ unobserved quality $\theta \in \mathbb{R}^2$ have two dimensions: drug effectiveness $h \in \mathbb{R}$ and how well it represses side effects $s \in \mathbb{R}$. The utility an individual gets from consuming drug d, conditional on all observed objective qualities $\mathbf{X}$ is given by:[1][2]

$$u_d(h, s|\mathbf{X}) = \alpha h + \beta s + \gamma(\text{AIDS} \cdot h), \tag{C.1}$$

[1] We write our theoretical model after conditioning on all observed characteristics of the drug to understand how drug demand relates to unobserved qualities of the drug and expert comments. We categorize the drug's unobserved qualities into two dimensions, effectiveness and side effects, which may be correlated with observed measures of drug effectiveness (probability of non-decreasing CD4 count) and side effects (probability of no ailment).

[2] We have suppressed the individual subscript i to simplify notation.

where AIDS is a dummy for whether the individual is suffering from AIDS and $\alpha > 0, \beta > 0, \gamma > 0$.[3] We assume that the individual does not observe θ, and uses reviews from doctors and activists as signals of the true unobserved quality. Let us assume that h and s can take one of two values, $h \in \{h^H, h^L\}$ and $s \in \{s^H, s^L\}$, where H denotes high quality and L denotes low quality, and doctor and activist comments can either be high or low, i.e., $D, A \in \{0, 1\}$ where 0 denotes low comment and 1 denotes high comment. Then, we can define probabilities for observing quality $t \in \{H, L\}$, conditional on doctor and activist comments as:

$$P_d(h = h^H | R = r) = p_R^r, \tag{C.2}$$

$$P_d(s = s^H | R = r) = q_R^r, \tag{C.3}$$

$R \in \{D, A\}, r \in \{0, 1\}$. Moreover, we assume that conditional on both observed and unobserved drug characteristics doctor's and activist's comment are independent. Given this setup, we can now derive theoretical predictions that can be tested empirically.

Proposition 5. *When the doctor and activist agree, individuals choose the drug that gets a high comment, provided that comments are informative.*

Proof. Individuals will choose the drug that gives them the highest expected utility.

[3] This restriction on preference parameters assumes that individuals prefer drugs that are more effective and have less side effects, and that these are state-dependent preferences for effectiveness, in that individuals with AIDS prefer more effective drugs more [110].

Suppose drug k gets high comments from both experts, while drug j gets low comments from both experts. An individual, regardless of his AIDS status, will choose drug k over j when

$$E[u_k(h, s|\mathbf{X}, D, A)] > E[u_j(h, s|\mathbf{X}, D, A)] \tag{C.4}$$

$$\begin{aligned}\Leftrightarrow (\alpha + \gamma\text{AIDS})h^H(p_D^1 - p_D^0 + p_A^1 - p_A^0) + \beta s^H(q_D^1 - q_D^0 + q_A^1 - q_A^0) > \\ (\alpha + \gamma\text{AIDS})h^L(p_D^1 - p_D^0 + p_A^1 - p_A^0) + \beta s^L(q_D^1 - q_D^0 + q_A^1 - q_A^0).\end{aligned} \tag{C.5}$$

The last inequality is always true when $p_D^1 > p_D^0$, $p_A^1 > p_A^0$, $q_D^1 > q_D^0$ and $q_A^1 > q_A^0$. In words, both experts are more likely to give a higher rating to drugs that are better on both dimensions. □

Proposition 6. *When the doctor and activist disagree, we will observe differences in responses to conflicts depending on health status if and only if*

1. *individuals without AIDS value low side effects more than high effectiveness* $(\beta > \alpha)$,
2. *individuals with AIDS value high effectiveness more than low side effects* $(\beta < (\alpha + \gamma))$,
3. *the activist puts more weight on side effects than the doctor* ($q_D^0 > q_D^1$ *and* $q_A^1 > q_A^0$),

4. the relative probability that the activist gives a high rating to a drug that has high h is lower than the relative probability of the doctor doing the same ($(p_A^1 - p_A^0) < (p_D^1 - p_D^0)$).

Proof. Suppose the doctor gives a low comment to drug k and a high comment to drug j, while the activist gives a high comment to drug k and a low comment to drug j. Then, an individual without AIDS will choose drug k when

$$\begin{aligned}\implies \alpha h^H(p_D^0 - p_D^1 + p_A^1 - p_A^0) + \beta s^H(q_D^0 - q_D^1 + q_A^1 - q_A^0) &> \\ \alpha h^L(p_D^0 - p_D^1 + p_A^1 - p_A^0) + \beta s^L(q_D^0 - q_D^1 + q_A^1 - q_A^0)&\end{aligned} \tag{C.6}$$

Given that $h^H > h^L$ and $s^H > s^L$, under these assumptions, equation (15) will be satisfied if $(p_A^1 - p_A^0) > (p_D^1 - p_D^0)$. If $(p_A^1 - p_A^0) < (p_D^1 - p_D^0)$, then for equation (15) to be satisfied, $\beta > \alpha$, so that the expected marginal utility from higher s is greater than the expected marginal utility from higher h.

An individual with AIDS = 1 will choose drug j over drug k if

$$\begin{aligned}(\alpha+\gamma) h^H(p_D^0 - p_D^1 + p_A^1 - p_A^0) + \beta s^H(q_D^0 - q_D^1 + q_A^1 - q_A^0) &< \\ (\alpha+\gamma) h^L(p_D^0 - p_D^1 + p_A^1 - p_A^0) + \beta s^L(q_D^0 - q_D^1 + q_A^1 - q_A^0)&\end{aligned} \tag{C.7}$$

It is easy to see that equation (16) will be satisfied when $(p_A^1 - p_A^0) < (p_D^1 - p_D^0)$, $\alpha, \beta, \gamma > 0$, and $\beta < (\alpha + \gamma)$, so that the expected marginal utility from higher s is lower than the expected marginal utility from higher h.

Now lets suppose $(p_A^1 - p_A^0) < (p_D^1 - p_D^0)$, $q_D^0 > q_D^1$, $q_A^1 > q_A^0$ and that for people without AIDS $\beta > \alpha$ while for people with AIDS $\beta < (\alpha + \gamma)$.

An individual without AIDS will choose drug k (for which the activist's comment is higher than the doctor's) when equation (15) is satisfied. Given our assumption that $h^H > h^L$ and $s^H > s^L$ and the above conditions, we can see that since $\beta > \alpha$, the LHS of the equation (15) is greater than the RHS. Individuals with AIDS, however, will choose drug j (for which the doctor's comment is higher than the activist's) when equation (16) is satisfied. Given that we assume that $\alpha, \beta, \gamma > 0$, and following the above conditions, we can see that equation (16) is satisfied.

$\square$

C.2 Data Collection

C.2.1 *Positively Aware* Data Dictionary

In this section, we present a data dictionary for the constructed dataset from the *Positively Aware* magazines. Below is a list of variables that we derived from the magazines, along with a description of what that variable measures.

- ↪ Common Name - This codes the generic name of the drug.
- ↪ Brand Name - This variable codes the brand name under which the drug is sold.
- ↪ Class - Class of drugs that the drug belongs to.
- ↪ Manufacturer - Name of the manufacturer.
- ↪ Public - A binary variable, indicating whether the drug company is publicly traded.
- ↪ Year - Year the magazine was published.
- ↪ No. of Side Effects - Number of side effects for the drug listed in the drug guide.
- ↪ No. of Drug Interactions - Number of drug interactions with other drugs listed in the drug guide.
- ↪ Pill Burden - Number of tablets that need to be taken together.
- ↪ Dosage Frequency - Number of times a day the drug dose needs to be taken.

↪ Food Restrictions - A binary variable indicating whether drug intake has any food restrictions.

↪ Annual Cost - Average Wholesale Price of drugs, as specified by the manufacturer

↪ DHHS Preferred - A binary variable, indicating whether the drug has been approved as first-line therapy by the Department of Health and Human Services.

↪ Doctor's Rating - A categorical variable that encapsulates a doctor's rating of the drug on a scale of 1 to 3.

1. Doctor mainly uses negative words or phrases to describe the drug.
2. Doctor says positive things, with some qualifications.
3. Doctor says mostly positive things.

↪ Activist's Rating - A categorical variable that encapsulates the activist's rating of the drug on a scale of 1 to 3.

1. Activist mainly uses negative words or phrases to describe the drug.
2. Activist says positive things, with some qualifications.
3. Activist says mostly positive things.

↪ Doctor - The variable codes the name of the doctor who has reviewed for the current issue of the drug guide.

↪ Activist - The variable codes the name of the activist who has reviewed for the current issue of the drug guide.

Table C.16 presents a summary of all the drugs in the dataset, along with their manufacturer details and year of entry and exit.

Doctor and Activist Reviews

In order to create a ranking system for the reviews, we use the following set of criteria:

↪ Assign a rating of 1 if mostly negative words or phrases have been used to describe the drug. For example, comments such as "*There is* ***not much to say*** *about ddC anymore."* ... *"**hard to get excited about it**, and these days it's often not prescribed.*" ... "*The role for delavirdine* ***remains unclear***.", or an activist's comments such as "*ddC has* ***never lived up to its initial promise***" ... "***overall, not a very useful drug***" ... "*Invirase was* ***extraordinarily weak*** ... ***not much reason to take it.*** " would be assigned a rank of 1.

↪ Assign a rating of 2 if the doctor or advocate points out the positive as well as the negative aspects of the drug, but does not give an absolute recommendation of whether the drug is good or bad. For example, comments of the form "*The new soft-gel formulation achieves* ***much better drug levels*** ... *but if you are going to use Fortovase as a sole PI,* ***you will have to take a lot of pills***.", and "*It may not be the best bet to include in first-line treatment ...* ***but it remains a solid antiviral.***"

↪ Assign a rank of 3 to drugs with reviews that mostly use positive words to describe the drug. For example, "*3TC is a* ***potent, convenient and well-tolerated drug***" or, "*3TC, with its* ***minimal side effects, easy dosing schedule and high potency****, may be the* ***most useful of the nucleosides***" would receive a rank of 3.

C.3 Demand Estimation

We estimate the demand model by GMM, matching the moments predicted by the model to the sample moments. We match two sets of moments to their sample analogue: (1) the market shares for all combinations, and (2) the covariance of the observed product characteristics, $\mathbf{x}$, with the observed individual-level characteristics, $\mathbf{z}$.

For computational ease, we assume that the ϵ_{ijt}'s have an independently and identically distributed extreme value distribution, which leads to the familiar closed-form for the model's choice probabilities conditional on $\mathbf{z}$:

$$\Pr_t(y = j|\mathbf{x}, \mathbf{z}, \boldsymbol{\theta}) = \frac{\exp\left(\delta_{jt} + \sum_{kr} x_{jtk} z_{ir} \beta_{kr}\right)}{1 + \sum_q \exp\left(\delta_{qt} + \sum_{kr} x_{qtk} z_{ir} \beta_{kr}\right)} \tag{C.8}$$

In order to compute our moments, we first find the value of $\boldsymbol{\delta}$ that makes the market shares from the data, s_{jt}^N, equal to the market shares predicted by the model,[4] $s_{jt}(\boldsymbol{\delta}, \boldsymbol{\beta}; .)$, for each guess at $(\boldsymbol{\beta})$. We then substitute that $\boldsymbol{\delta}(\boldsymbol{\beta}, s_{jt}; .)$ for δ into the model's prediction for the micro moments, making them a function of $(\boldsymbol{\beta}, \boldsymbol{\delta}(\boldsymbol{\beta}, s_{jt}; ,))$. Lastly, we search over $(\boldsymbol{\beta})$ to minimize the distance between model's predictions for the micro moments and the data.

Recall that we also need to address the endogeneity problem of the reviews, since we expect reviews and ξ_{jt} to be correlated. The instruments we use are the average

[4]For the logit specification, that is simply equal to the log market share of combo c minus the log of the share of the outside option (taking no drugs).

combo characteristics of rival drugs on the market. Let $\boldsymbol{Z} = [Z_1, Z_2]$ be the set of instruments, where Z_1 is the average probability of no ailments for the rival drugs on the market, and Z_2 is the average probability of non-decreasing CD4 count for the rival drugs on the market.

We now describe our estimation algorithm in detail:

1. Let $\mathbf{z}_d$, for $d = 1, \ldots, ns$, be the individual-level characteristics for the ns individuals in visit t from the individual level data from MACS. We then define $\boldsymbol{\delta}^{ns,n}(\boldsymbol{\beta})$ as the value of $\boldsymbol{\delta}$ for a given value of $\boldsymbol{\beta}$ that sets

$$g_1^{ns,N}(\boldsymbol{\theta}) = s_{jt}^N - \frac{1}{ns}\sum_{d=1}^{ns} \mathrm{Pr}_t\left(y = j|\mathbf{x}, \mathbf{z}_d, \boldsymbol{\beta}, \boldsymbol{\delta}^{ns,n}(\boldsymbol{\beta})\right) \tag{C.9}$$

   equal to $\mathbf{0}$.

2. Calculate the model's prediction for the covariances between the characteristics of the chosen combination and individual-level attributes. In particular, to form the sample moment, we interact the average attributes of the individuals that chose combination j at time t with the characteristics of the combination at time t, and then average over all available combinations in that time period. Formally, the second moment is defined as:

$$g_2^{n,ns}(\boldsymbol{\theta}) \approx \frac{1}{n}\sum_j n_j x_{kj}\left\{\frac{\sum_{i_j=1}^{n_j} z_{i_j}}{n_j} - E\left[\mathbf{z}|y = j, \boldsymbol{\beta}, \boldsymbol{\delta}^{ns,n}(\boldsymbol{\beta})\right]\right\} \tag{C.10}$$

where

$$E[\mathbf{z}|y=j,\boldsymbol{\beta},\boldsymbol{\delta}^{ns,n}(\boldsymbol{\beta})] = \frac{(ns)^{-1}\sum_d \mathbf{z}_d \mathrm{Pr}_t(y=j|\mathbf{x},\mathbf{z}_d,\mathbf{v}_d,\boldsymbol{\beta},\boldsymbol{\delta}^{ns,n}(\boldsymbol{\beta}))}{s^n_{jt}}, \quad \text{(C.11)}$$

n_j is the number of individuals taking combination j, $n = \sum_j n_j$ and $\mathrm{Pr}_t(y=j|\mathbf{x},\mathbf{z}_d,\mathbf{v}_d,\boldsymbol{\beta},\boldsymbol{\delta}^{ns,N}(\boldsymbol{\beta}))$ is given by equation (C.8).

3. Calculate $\bar{\beta}_k$ using the IV GMM formula, and then, using $\boldsymbol{\delta}^{ns,n}(\boldsymbol{\beta})$ from step 1, calculate the error term as

$$\omega_{jt}(\boldsymbol{\theta}) = \boldsymbol{\delta}^{ns,n}(\boldsymbol{\beta}) - \sum_k x_{jtk}\bar{\boldsymbol{\beta}}, \quad \text{(C.12)}$$

to calculate the third moment, which is given by:

$$g_3 = E[\boldsymbol{Z}\omega(\boldsymbol{\theta})] = 0 \quad \text{(C.13)}$$

4. Find the generalized method of moments estimator of $(\boldsymbol{\theta}_{GMM}) = (\boldsymbol{\beta_{GMM}}, \bar{\boldsymbol{\beta}}_{\boldsymbol{GMM}})$ from stacking g_2 and g_3 into a single vector f. In particular, we use a two-step estimation procedure with

$$(\boldsymbol{\beta_{GMM}}, \bar{\boldsymbol{\beta}}_{\boldsymbol{GMM}}) = argmin\left(\frac{1}{n}\sum_{i=1}^{n} f(\theta)\right)^T \hat{W}\left(\frac{1}{n}\sum_{i=1}^{n} f(\theta)\right) \quad \text{(C.14)}$$

where $W = E[f(\theta)f(\theta)']$. With the optimal weight matrix, the variance-covariance of the parameters $\boldsymbol{\theta_{GMM}}$ is given by:

$$\hat{V}(\boldsymbol{\theta_{GMM}}) = (\hat{G}^T \hat{W} \hat{G})^{-1} \tag{C.15}$$

C.4 Additional Robustness Checks

For additional robustness checks, we begin by pooling the doctor and activist reviews. Table C.17 presents the results of the logit with instruments for two ways of pooling the reviews: adding the two reviews for each combination, and taking the maximum of the two reviews for each drug. For both measures, we find that even after controlling for objective qualities, an increase in reviews leads to an increase in the likelihood of choosing the drug combination.

In Table C.18, we report results for the specification in which we control for individual and time fixed effects when predicting the probabilities of non-decreasing CD4 count and no ailment for each individual. As before, doctors' and activists' reviews positively predict demand independently; however, in the specification in which we control for both the activists' and doctors' reviews together and control for the combination's objective qualities, we find that a higher review from the doctor decreases the probability of choosing that combination while a higher review by the activist for a combination leads to an increase in the probability of that combination being demanded. The disagreement results are the same, yet in this specification the interaction between the doctors' review and disagreement is not significant.

Lastly, we also check if our mechanism for explaining the negative coefficient on doctor's review is robust to how we define the reviews. Therefore, we use the definition for reviews in which we calculate the percentage of drugs in a combination that have a rating of 3 as our measure of combo-level reviews and run the specification with agreements and disagreements between the two experts. Table C.19, column (1) replicates the results for this definition of reviews with which we find that after we control for the activist's review and the objective qualities, the doctor's review negatively affects demand. In column (2), we find that if the experts agree about a combination, then a higher review increases the likelihood of taking that combination. However, in the case of a disagreement, a higher activist's review leads to an increase in the likelihood of taking the combination while a higher doctor's review decreases the likelihood of taking that combination (though the effect is not significant). In column (3), we explore the non-linearities in disagreements and find that if the activist gives a lower review to the combination than the doctor (i.e. a smaller percentage of drugs in the combo receive a rating of 3 from the activist), and the activist's review increases, then the probability of consuming that combination increases.

C.5 State of the Market

The tables in this section show summary statistics and tabulations for the state of the market over time.

C.6 Tables

Table C.1: Summary Statistics: MACS Dataset (Individual Level Variables)

	Mean	Std. Dev.	Min	Max
CD4 Count	536.4	283.9	5	3819
Non-decreasing CD4	0.54	0.50	0	1
No Ailment	0.63	0.48	0	1
AIDS	0.20	0.40	0	1
Age	47.15	8.21	19.5	80
Work Full-time	0.54	0.50	0	1
White	0.54	0.50	0	1
High School	0.19	0.39	0	1
College	0.50	0.50	0	1
Obs	13,472			

Notes: Summary statistics for the Multi-center AIDS Cohort Study (MACS) variables, which consists of 13,472 patient-visit observations. We restrict our sample to the years 1997-2008.

Table C.2: Summary Statistics: Positively Aware Drug Guides Data

	Mean	Std. Dev.	Min	Max
Annual Cost	6690	4180	875	28007
No. of Side Effects	13.16	6.10	1	33
No. of Drug Interactions	14.26	10.34	0	43
Food Restrictions	0.34	0.48	0	1
Pill Burden (per take)	2.15	1.86	1	8
Dosage Frequency (per day)	1.94	0.65	1	3
DHHS Preferred	0.27	0.25	0	1
Publicly Traded Manuf.	0.90	0.28	0	1
Doctor's Rating	2.02	0.74	1	3
Activist's Rating	1.89	0.77	1	3
Disagreement	0.39	0.49	0	1
Obs	197			

Notes: Summary statistics for drug-level variables constructed using the Positively Aware annual drug guide, which consists of 197 drug-year observations. We restrict our sample to the years 1997-2008, and to drugs that have been FDA approved and can be matched to treatments observed in the MACS dataset. Doctor and activists' rating can take values 1, 2 or 3.

Table C.3: Relating Reviews with PA Characteristics

	OLS		Ordered Probit	
	Doctor	Activist	Doctor	Activist
No. of Side Effects	-0.01	-0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.00)	(0.00)
No. of Drug Interactions	-0.01	-0.01	-0.01	-0.01*
	(0.01)	(0.01)	(0.00)	(0.00)
Food Restrictions	-0.01	0.17	-0.00	0.09
	(0.12)	(0.13)	(0.01)	(0.06)
Pill Burden	0.10***	-0.00	0.05***	-0.00
	(0.03)	(0.04)	(0.02)	(0.02)
Dosage Frequency	-0.33***	-0.21**	-0.18***	-0.10**
	(0.08)	(0.09)	(0.05)	(0.04)
Publicly Traded	0.01	-0.24	-0.00	-0.12
	(0.18)	(0.18)	(0.10)	(0.10)
Nobs.	197	197	197	197

Notes: *, **, *** denote p-value < 0.10, 0.05, and 0.01, respectively. Standard errors are given in parentheses. Drug-visit dyad is the unit of analysis. The left-hand-side variable is either Doctor's or Activist's review (taking values 1, 2, or 3). Columns (3) and (4) report marginal effects for the ordered probit.

Table C.4: Relationship between Reviews and Demand - Drug Level

	(1)	(2)	(3)	(4)
Doctor's Review	0.02***		0.01***	0.01***
	(0.00)		(0.00)	(0.00)
Activist's Review		0.03***	0.02***	0.02***
		(0.00)	(0.00)	(0.00)
Average Doctor Reviews of Other Drugs in Combo				-0.01***
				(0.00)
Average Activist Reviews of Other Drugs in Combo				0.01***
				(0.00)
PA Characteristics	Y	Y	Y	Y
Nobs.	33,608	33,608	33,608	33,608

Notes: *, **, *** denote p-value < 0.10, 0.05, and 0.01, respectively. Standard errors are given in parentheses. Individual-drug-visit is the unit of analysis. The left-hand-side variable is drug-level market shares, defined as the fraction of people taking a particular drug out of the total number of HIV+ men in the sample.

Table C.5: Summary Statistics: Combo Level

	Mean	Std. Dev.	Min	Max
(a) Reviews				
Doctor Average	2.18	0.57	0	3
Activist Average	2.07	0.56	0	3
Doctor Std. Dev.	0.51	0.38	0	1.41
Activist Std. Dev.	0.60	0.36	0	1.41
% of 3's - Doctor	0.37	0.34	0	1
% of 3's - Activist	0.32	0.30	0	1
% of 2's - Doctor	0.47	0.34	0	1
% of 2's - Activist	0.45	0.31	0	1
% of 1's - Doctor	0.14	0.23	0	1
% of 1's - Activist	0.21	0.26	0	1
Disagreement	0.62	0.49	0	1
(b) Objective Qualities				
Probability of Non-decreasing CD4	0.55	0.15	0	1
Probability of No Ailment	0.60	0.19	0	1
(c) Market Shares				
Combos	0.01	0.02	0	0.18
Fringe	0.32	0.05	0.23	0.42
Outside Option (No Drug)	0.19	0.04	0.12	0.27
Obs	1086			

Notes: Panel (a) reports summary statistics for combo-level variables constructed using the Positively Aware annual drug guide. Panels (b) and (c) report combo-level variables constructed using the MACS dataset. The probability of non-decreasing CD4 count and probability of no ailment are constructed by averaging data across all individuals for each combo in every visit. Combos in the 'Fringe' category at a particular visit are taken by fewer than 25 individuals in that visit.

Table C.6: Qualities and Combo Demand

	(1)	(2)	(3)	(4)	(5)	(6)
Prob of No Ailment	1.02***		1.05***	0.95***		0.97***
	(0.20)		(0.20)	(0.19)		(0.19)
Prob of Non-decreasing CD4		0.80***	0.87***		0.63**	0.68***
		(0.27)	(0.26)		(0.25)	(0.25)
No. of Side Effects				-0.09***	-0.09***	-0.09***
				(0.01)	(0.01)	(0.01)
No. of Drug Interactions				0.00	0.00	0.00
				(0.01)	(0.01)	(0.01)
Pill Burden				-0.02	-0.03**	-0.03*
				(0.01)	(0.01)	(0.01)
Food Restrictions				-0.41**	-0.49***	-0.41**
				(0.17)	(0.17)	(0.17)
Dosage				-0.21***	-0.25***	-0.21***
				(0.08)	(0.08)	(0.08)
Combo-visit dyads	1086	1086	1086	1086	1086	1086

Notes: *, **, *** denote p-value < 0.10, 0.05, and 0.01, respectively. Standard errors are given in parentheses. Combo-visit dyad is the unit of analysis. The left-hand-side variable is combo-level market shares. Probability of no ailment and probability of non-decreasing CD4 count are combo characteristics constructed using the MACS dataset, while all other combo-characteristics are constructed using the Positively Aware annual drug guide by averaging across all drugs in a combo.

Table C.7: Qualities and Reviews

	Doctor			Activist		
	(1)	(2)	(3)	(4)	(5)	(6)
Prob of No Ailment	0.48***		0.33***	0.55***		0.39***
	(0.08)		(0.08)	(0.08)		(0.07)
Prob of Non-decreasing CD4		1.22***	1.15***		1.37***	1.29***
		(0.10)	(0.10)		(0.09)	(0.09)
Combo-visit dyads	1086	1086	1086	1086	1086	1086

Notes: *, **, *** denote p-value < 0.10, 0.05, and 0.01, respectively. Standard errors are given in parentheses. Combo-visit dyad is the unit of analysis. The left-hand-side variable is either Doctor's or Activist's review (taking values between 0 and 3, where expert review = 0 for the outside option).

Table C.8: Reviews and Combo Demand with PA Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
Doctor's Review	0.16**	0.17***			-0.16*	-0.11
	(0.06)	(0.06)			(0.09)	(0.09)
Activist's Review			0.36***	0.35***	0.48***	0.43***
			(0.07)	(0.07)	(0.10)	(0.10)
Prob of No Ailment		1.01***		0.99***		0.97***
		(0.19)		(0.18)		(0.19)
Prob of Non-decreasing CD4		0.59**		0.40		0.40
		(0.25)		(0.25)		(0.25)
No. of Side Effects	-0.09***	-0.09***	-0.09***	-0.09***	-0.09***	-0.09***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
No. of Drug Interactions	0.00	0.00	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Pill Burden	-0.03**	-0.03**	-0.02*	-0.02	-0.02	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Food Restrictions	-0.49***	-0.40**	-0.59***	-0.51***	-0.63***	-0.54***
	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)
Dosage	-0.28***	-0.25***	-0.43***	-0.39***	-0.45***	-0.41***
	(0.08)	(0.08)	(0.09)	(0.09)	(0.09)	(0.09)
Nobs.	1086	1086	1086	1086	1086	1086

Notes: *, **, *** denote p-value < 0.10, 0.05, and 0.01, respectively. Standard errors are given in parentheses. Combo-visit dyad is the unit of analysis. The left-hand-side variable is combo-level market shares. Both experts' reviews are constructed by averaging over drug reviews in each combo.

Table C.9: Reviews and Own and Rival Objective Qualities

	Doctor				Activist			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Prob of No Ailment	0.48***		0.33***	0.35***	0.55***		0.39***	0.44***
	(0.08)		(0.08)	(0.07)	(0.08)		(0.07)	(0.07)
Prob of Non-decreasing CD4		1.22***	1.15***	1.18***		1.37***	1.29***	1.26***
		(0.10)	(0.10)	(0.10)		(0.09)	(0.09)	(0.09)
Avg Rivals' Prob of No Ailment				-3.90***				-4.51***
				(0.45)				(0.43)
Avg Rivals' Prob of Non-dec CD4				-2.20***				0.04
				(0.48)				(0.46)
Nobs.	1086	1086	1086	1086	1086	1086	1086	1086

Notes: *, **, *** denote p-value < 0.10, 0.05, and 0.01, respectively. Standard errors are given in parentheses. Combo-visit dyad is the unit of analysis. The left-hand-side variable is either Doctor's or Activist's review for a combo.

Table C.10: IV Logit Estimates - Baseline Specification

	(1)	(2)	(3)	(4)	(5)	(6)
Doctor's Review	1.38***	1.23***			-2.67***	-2.97***
	(0.34)	(0.33)			(0.87)	(0.90)
Activist's Review			2.12***	2.12***	4.08***	4.41***
			(0.33)	(0.34)	(0.75)	(0.81)
Prob of No Ailment		1.44***		1.40***		0.85**
		(0.25)		(0.27)		(0.37)
Prob of Non-decreasing CD4		0.14		-0.93**		-1.11**
		(0.36)		(0.45)		(0.56)
No. of Individuals	13,472	13,472	13,472	13,472	13,472	13,472
Combo-time dyads	1086	1086	1086	1086	1086	1086

Notes: *, **, *** denote p-value < 0.10, 0.05, and 0.01, respectively. Standard errors are given in parentheses. The table reports the logit coefficients. The left-hand-side variable is combo-level market shares. Doctor's and Activist's reviews have been instrumented using the average probability of no ailment and average probability of non-decreasing CD4 count of rival combos. Combo-visit dyad is the unit of analysis. The total number of combo-visit observations used for the estimation is 1,086, which are constructed using data on 13,472 individuals.

Table C.11: Baseline Estimates - Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)
(a) Percentage of High Reviews						
% of 3's - Doctor	2.14***	2.16***			-2.39***	-2.43***
	(0.53)	(0.52)			(0.89)	(0.90)
% of 3's - Activist			3.21***	3.30***	4.48***	4.64***
			(0.39)	(0.40)	(0.65)	(0.67)
Prob of No Ailment		1.27***		1.29***		1.15***
		(0.22)		(0.22)		(0.26)
Prob of Non-decreasing CD4		0.64**		-0.06		-0.18
		(0.29)		(0.31)		(0.36)
(b) Percentage of High and Medium Reviews						
% of 3's - Doctor	3.62***	2.91***			-1.43	-1.44
	(0.77)	(0.72)			(1.22)	(1.19)
% of 2's - Doctor	2.88***	2.02***			-0.67	-0.75
	(0.81)	(0.76)			(1.31)	(1.30)
% of 3's - Activist			2.78***	2.83***	3.15***	3.36***
			(0.56)	(0.56)	(0.98)	(0.96)
% of 2's - Activist			-0.57	-0.73	-1.05	-0.91
			(0.71)	(0.68)	(1.17)	(1.13)
Prob of No Ailment		1.46***		1.29***		1.15***
		(0.25)		(0.22)		(0.28)
Prob of Non-decreasing CD4		0.05		0.19		0.41
		(0.39)		(0.39)		(0.42)
(c) Review Average and Standard Deviation						
Doctor's Review	2.23***	1.80***			-2.00*	-4.26
	(0.64)	(0.62)			(1.12)	(3.24)
Doctor's Review SD	-0.27	-2.23			0.34	-7.63
	(1.41)	(1.47)			(1.46)	(5.30)
Activist's Review			2.56***	2.56***	4.30***	4.11**
			(0.22)	(0.23)	(0.73)	(1.83)
Activist's Review SD			1.39*	0.58	2.45**	-2.82
			(0.79)	(0.92)	(1.06)	(3.75)
Prob of No Ailment		1.48***		1.05***		1.65*
		(0.26)		(0.22)		(0.85)
Prob of Non-decreasing CD4		0.28		-0.04		-1.84
		(0.36)		(0.36)		(1.67)
No. of Individuals	13,472	13,472	13,472	13,472	13,472	13,472
Combo-time dyads	1086	1086	1086	1086	1086	1086

Notes: *, **, *** denote p-value < 0.10, 0.05, and 0.01, respectively. Standard errors are given in parentheses. The table reports the logit coefficients. The left-hand-side variable is combo-level market shares. In panel (a), we use the percentage of drugs that receive a rating of 3 in a combo as a measure of 'high' reviews. In panel (b), we add the percentage of drugs that receive a rating of 2 in a combo as a measure of 'medium' reviews. In panel (c), our measure of reviews for the two experts includes the average across all drugs in a combo, as well as the standard deviation of reviews across drugs in a combo. In all cases, we use the average objective qualities (probability of no ailment and probability of non-decreasing CD4 count) of rival combos as instruments for reviews. Combo-visit dyad is the unit of analysis. The total number of combo-visit observations used for the estimation is 1,086, which are constructed using data on 13,472 individuals.

Table C.12: Mechanisms

	(1)	(2)	(3)
Doctor's Review	-2.97***		
	(0.90)		
Activist's Review	4.41***		
	(0.81)		
Agree × Review		1.68***	1.62***
		(0.49)	(0.59)
Disagree × Activist's Review		2.92***	
		(0.54)	
Disagree × Doctor's Review		-2.07*	
		(1.08)	
Agree		-2.03	4.48
		(2.50)	(2.80)
Positive Difference × Doctor			-3.59
			(15.42)
Negative Difference × Doctor			-5.32*
			(3.00)
Positive Difference × Activist			6.14
			(11.74)
Negative Difference × Activist			10.83***
			(3.53)
Prob of No Ailment	0.85**	1.15***	0.71
	(0.37)	(0.31)	(0.61)
Prob of Non-decreasing CD4	-1.11**	-0.83*	-1.95*
	(0.56)	(0.48)	(1.01)
No. of Individuals	13,472	13,472	13,472
Combo-time dyads	1086	1086	1086

Notes: *, **, *** denote p-value $<$ 0.10, 0.05, and 0.01, respectively. Standard errors are given in parentheses. The table reports the logit coefficients. The left-hand-side variable is combo-level market shares. Doctor's and Activist's review have been instrumented using the average probability of no ailment and average probability of non-decreasing CD4 count of rival combos. The variable 'Agree' is a dummy which is 1 if both experts give the same rating to a combo. The variable 'Disagree' is a dummy which is 1 if each expert gives a different rating to a combo. Finally, the variable 'Positive Difference' is a dummy which is 1 if the doctor's review is lower than the activist's review, while the variable 'Negative Difference' is a dummy which is 1 if the doctor's review is higher than the doctor's review. Combo-visit dyad is the unit of analysis. The total number of combo-visit observations used for the estimation is 1,086, which are constructed using data on 13,472 individuals.

Table C.13: Reviews and Objective Qualities when Experts Disagree

	Doctor	Activist
Prob of No Ailment	-0.04	0.18**
	(0.09)	(0.08)
Prob of Non-decreasing CD4	0.19*	0.50***
	(0.11)	(0.11)
Avg Rivals' Prob of No Ailment	-1.89***	-3.79***
	(0.54)	(0.52)
Avg Rivals' Prob of Non-dec CD4	-1.56***	1.28***
	(0.50)	(0.48)
Nobs.	671	671

Notes: *, **, *** denote p-value $<$ 0.10, 0.05, and 0.01, respectively. Standard errors are given in parentheses. Combo-visit dyad is the unit of analysis. The sample is restricted to cases in which the two experts' ratings are different from each other. The left-hand-side variable is either Doctor or Activist's review.

Table C.14: Correlation between Objective Qualities

				Difference	
Combo Age	Full Sample	Agree	Disagree	Positive	Negative
0–3 Years	-0.09*	0.07	-0.13*	-0.25*	-0.07
4–7 Years	-0.05	0.08	0.07	-0.23*	0.21*
8–11 Years	0.18	0.27*	-0.14	-0.40	-0.06

Notes: The table reports correlations between probability of no ailment and probability of non-decreasing CD4 count for different brackets of combo age. Column (1) reports the correlations for the full sample, column (2) reports correlations for the sample in which both experts' rating is the same, and column (3) reports the correlations for the sample in which both experts' rating for a combo is different. Finally, column (4) reports the correlations for cases in which the activist's review is higher than doctor's review, and column (5) reports the correlations for cases in which the activist's review is lower than the doctor's review. *, **, *** denote p-value $<$ 0.10, 0.05, and 0.01, respectively.

Table C.15: Demand Model with Individual Attributes

Demand Side Parameters	Variable	Estimates	Std. Errors
Means (β)	Doctor's Review	-5.86	0.00
	Activist's Review	3.15	0.04
	Constant	5.94	0.13
	Prob of No Ailment	0.70	0.00
	Prob of Non-decreasing CD4	0.40	0.01
Individual Attributes	AIDS	0.06	0.05
	Age	0.20	0.13
	Full-time work	-1.59	0.67
	Black	-0.17	0.18
	College	0.50	0.03
	Same Combo Last Period - Fringe	-0.32	0.19
	Same Combo Last Period - Other	2.00	1.90
Interactions with Individual Attributes	Doctor's Review $\times$ AIDS	9.50	2.38
	Doctor's Review $\times$ Age	0.26	0.01
	Doctor's Review $\times$ Full-time work	-1.32	0.99
	Doctor's Review $\times$ Black	-2.05	2.02
	Doctor's Review $\times$ College	3.41	1.25
	Doctor's Review $\times$ SC - Fringe	-3.72	0.49
	Doctor's Review $\times$ SC - Other	3.32	1.43
	Activist's Review $\times$ AIDS	1.48	1.25
	Activist's Review $\times$ Age	0.38	0.31
	Activist's Review $\times$ Full-time work	0.55	0.22
	Activist's Review $\times$ Black	-0.06	0.05
	Activist's Review $\times$ College	-0.30	0.28
	Activist's Review $\times$ SC - Fringe	-5.47	0.84
	Activist's Review $\times$ SC - Other	4.33	1.76

Notes: The table reports coefficients for the IV-logit demand model with individual characteristics. Combo-visit dyad is the unit of analysis. The left-hand-side variable is combo-level market shares. Doctor's review, activist's review, probability of no ailment and probability of non-decreasing CD4 count vary only over combo and visit. The variable 'Same Combo Last Period - Fringe' is a dummy for whether the individual taking a fringe combo was also taking a combo from the fringe group (combinations taken by less than 25 individuals in a visit) in the last visit, and 'Same Combo Last Period - Other' is a dummy which is 1 if the individual was taking the same combo (including the outside option) last visit that he is taking in the current period. The model is estimated using Generalized Method of Moments (GMM).

Table C.16: Drug Information

	Manufacturer	Year of Introduction	Year of Discontinuation
(a) NRTI			
Retrovir	GlaxoSmithKline	1987	-
Videx	Bristol-Myers Squibb	1997	-
Hivid	Hoffman-LaRoche	1997	2006
Zerit	Bristol-Myers Squibb	1997	-
Epivir	GlaxoSmithKline	1997	-
Combivir	GlaxoSmithKline	1998	-
Ziagen	GlaxoSmithKline	1999	-
Viread	Gilead Sciences	2000	-
Trizivir	GlaxoSmithKline	2001	-
Emtriva	Gilead Sciences	2004	-
Epzicom	GlaxoSmithKline	2004	-
Truvada	Gilead Sciences	2004	-
(b) NNRTI			
Viramune	Boehringer Ingelheim	1997	-
Rescriptor	Agouron Pharmaceuticals	1997	-
Sustiva	Bristol-Myers Squibb	1998	
(c) PI			
Norvir	Abbott Laboratories	1997	-
Crixivan	Merck & Company	1997	-
Viracept	Agouron Pharmaceuticals	1997	-
Saquinavir	Hoffman-LaRoche	1997	-
Agenerase	GlaxoSmithKline	1999	-
Kaletra	Abbott Laboratories	2000	-
Aptivus	Boehringer Ingelheim	2001	-
Reyataz	Bristol-Myers Squibb	2002	-
Lexiva	GlaxoSmithKline	2004	-
Prezista	Tibotec Therapeutics	2004	-

Notes: The table lists details about all drugs in the sample, grouped by drug type. HIV drugs belong to three drug types: Nucleoside Reverse Transcriptase Inhibitor (NRTI), Non-nucleoside Reverse Transcriptase Inhibitor (NNRTI) and Protease Inhibitor (PI). During our period of analysis, only one drug was discontinued.

Table C.17: IV Logit Estimates - Pooling Reviews

	(1)	(2)	(3)	(4)
Total	0.55***	0.62***		
	(0.16)	(0.16)		
Max			0.95***	1.06***
			(0.26)	(0.25)
Objective Qualities	N	Y	N	Y
No. of Individuals	13,472	13,472	13,472	13,472
Combo-time dyads	1,086	1,086	1,086	1,086

Notes: *, **, *** denote p-value < 0.10, 0.05, and 0.01, respectively. Standard errors are given in parentheses. The left-hand-side variable is combo-level market shares. Doctor's review and Activist's review have been pooled together and instrumented using the average probability of no ailment and average probability of non-decreasing CD4 count of rival combos. Columns (1) and (2) show results for the specification in which the two experts' reviews have been pooled by adding up the reviews, while columns (3) and (4) show results for the specification in which the maximum of the two experts' reviews is used as the measure of combo review. The total number of observations used for the estimation is 1,086, which are constructed using data on 13,472 individuals. Objective qualities include the probability of no ailment and probability of non-decreasing CD4 count of the combo.

Table C.18: Objective Qualities with Individual and Time Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Doctor's Review	1.64***	1.49***			-0.79	-2.60***	
	(0.38)	(0.34)			(0.77)	(1.00)	
Activist's Review			2.01***	1.08***	2.63***	4.26***	
			(0.36)	(0.21)	(0.71)	(0.93)	
Agree × Review							1.60***
							(0.46)
Disagree × Activist's Review							3.00***
							(0.56)
Disagree × Doctor's Review							-1.10
							(1.01)
Agree							0.49
							(2.47)
Objective Qualities	N	Y	N	Y	N	Y	Y
N	1086	1086	1086	1086	1086	1086	1086

Notes: *, **, *** denote p-value < 0.10, 0.05, and 0.01, respectively. Standard errors are given in parentheses. The left-hand-side variable is combo-level market shares. Objective qualities include the probability of no ailment and the probability of non-decreasing CD4 count of the combo, which are constructed by controlling for individual and time fixed effects when predicting the probabilities using individual-level data from MACS. Doctor's and Activist's review have been instrumented using the average probability of no ailment and average probability of non-decreasing CD4 count of rival combos. The variable 'Agree' is a dummy which is 1 if both experts give the same rating to a combo. The variable 'Disagree' is a dummy which is 1 if each expert gives a different rating to a combo.

Table C.19: DISAGREEMENTS

	(1)	(2)	(3)
Doctor's Review	-2.43***		
	(0.90)		
Activist's Review	4.64***		
	(0.67)		
Agree × Review		3.07***	3.09***
		(0.57)	(0.65)
Disagree × Activist's Review		2.59***	
		(0.57)	
Disagree × Doctor's Review		-1.71	
		(1.70)	
Agree (% High)		-0.90	-1.06
		(0.89)	(0.85)
Positive Difference × Doctor			7.86**
			(3.61)
Negative Difference × Doctor			-3.40
			(2.09)
Positive Difference × Activist			-1.42
			(2.05)
Negative Difference × Activist			9.96***
			(3.06)
Objective Qualities	Y	Y	Y
No. of Individuals	13,472	13,472	13,472
Combo-time dyads	1086	1086	1086

Notes: *, **, *** denote p-value < 0.10, 0.05, and 0.01, respectively. Standard errors are given in parentheses. The left-hand-side variable is combo-level market shares. Doctor's and Activist's review have been instrumented using the average probability of no ailment and average probability of non-decreasing CD4 count of rival combos. The total number of observations used for the estimation is 1,086, which are constructed using data on 13,472 individuals. The variable 'Agree' is a dummy which is 1 if both experts give the same rating to a combo. The variable 'Disagree' is a dummy which is 1 if each expert gives a different rating to a combo. Finally, the variable 'Positive Difference' is a dummy which is 1 if the doctor's review is lower than the activist's review, while the variable 'Negative Difference' is a dummy which is 1 if the doctor's review is higher than the doctor's review. Objective qualities include the probability of no ailment and probability of non-decreasing CD4 count of the combo.

Table C.20: New Drugs

Date of Entry	Name	Market Share at time of entry
April, 1997	Videx	4.40%
April, 1999	Efavirenz	5.84%
April, 1999	Ziagen	0.76%
October, 2000	Kaletra	0.28%
October, 2001	Viread	0.62%
April, 2002	Trizivir	1.67%
October, 2003	Reyataz	0.71%
October, 2003	Emtriva	0.71%
April, 2005	Lexiva	0.56%
April, 2005	Truvada	6.60%
April, 2005	Epzicom	1.88%
October, 2006	Prezista	0.37%
April, 2008	Atripla	19.0%

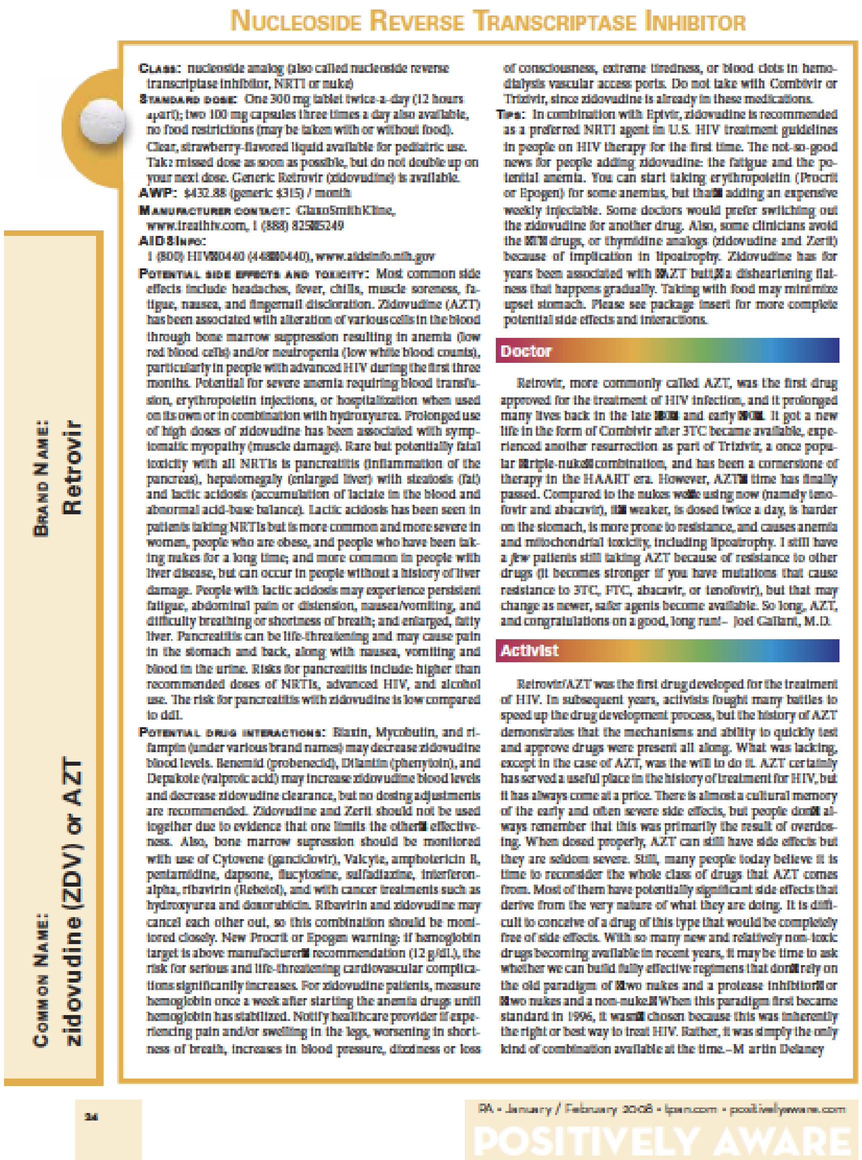
Notes: The table lists all new drugs that enter the HIV drug market during our period of analysis (1997-2008), along with the market share of those drugs at the time of entry. Market share is calculated at the combo level; i.e. for each of the drugs listed, the market share for drug i is the combined market share of all combinations that include drug i.

Table C.21: OBJECTIVE QUALITIES AND REVIEWS OF NEW ENTRANTS AND RIVALS AT TIME OF ENTRY

Reviews				
	Doctor		Activist	
	Own	Rival	Own	Rival
Videx	2.42	2.37	2.50	2.42
Efavirenz	2.78	2.28	2.16	2.15
Ziagen	2.92	2.32	2.00	2.16
Kaletra	2.33	1.97	2.67	2.41
Viread	2.83	2.52	2.33	2.38
Trizivir	3.00	2.26	2.17	2.09
Reyataz	2.20	2.36	2.00	2.11
Emtriva	2.17	2.36	2.17	2.11
Lexiva	2.33	2.20	2.33	1.91
Truvada	2.70	2.16	2.63	1.85
Epzicom	2.71	2.17	2.12	1.90
Prezista	2.33	1.91	2.33	1.80
Atripla	2.00	2.04	3.00	2.07
Objective Qualities				
	Non-Dec. CD4		No Ailment	
	Own	Rival	Own	Rival
Videx	0.54	0.57	0.56	0.63
Efavirenz	0.55	0.56	0.65	0.55
Ziagen	0.61	0.56	0.61	0.56
Kaletra	0.55	0.49	0.73	0.55
Viread	0.54	0.54	0.53	0.59
Trizivir	0.54	0.53	0.56	0.61
Reyataz	0.69	0.55	0.71	0.61
Emtriva	0.52	0.56	0.86	0.60
Lexiva	0.76	0.55	0.74	0.63
Truvada	0.62	0.55	0.70	0.62
Epzicom	0.64	0.55	0.61	0.63
Prezista	0.93	0.56	0.90	0.63
Atripla	0.61	0.60	0.81	0.60

Notes: The table reports the average reviews for each expert and objective qualities (probability of non-decreasing CD4 count and probability of no ailment) for the new entrants and their rivals at the time of entry. For any new entrant drug i, the columns labeled 'Own' report the average reviews (or objective quality measure) for all combinations that contain drug i. The columns labeled 'Rival' report the average review (or objective quality measure) for all combos other than the combos that contain drug i.

C.7 Figures



NUCLEOSIDE REVERSE TRANSCRIPTASE INHIBITOR

BRAND NAME: Retrovir

COMMON NAME: zidovudine (ZDV) or AZT

CLASS: nucleoside analog (also called nucleoside reverse transcriptase inhibitor, NRTI or nuke)

STANDARD DOSE: One 300 mg tablet twice-a-day (12 hours apart); two 100 mg capsules three times a day also available, no food restrictions (may be taken with or without food). Clear, strawberry-flavored liquid available for pediatric use. Take missed dose as soon as possible, but do not double up on your next dose. Generic Retrovir (zidovudine) is available.

AWP: $432.88 (generic $315) / month

MANUFACTURER CONTACT: GlaxoSmithKline, www.treathiv.com, 1 (888) 825-5249

AIDSINFO: 1 (800) HIV-0440 (448-0440), www.aidsinfo.nih.gov

POTENTIAL SIDE EFFECTS AND TOXICITY: Most common side effects include headaches, fever, chills, muscle soreness, fatigue, nausea, and fingernail discoloration. Zidovudine (AZT) has been associated with alteration of various cells in the blood through bone marrow suppression resulting in anemia (low red blood cells) and/or neutropenia (low white blood counts), particularly in people with advanced HIV during the first three months. Potential for severe anemia requiring blood transfusion, erythropoietin injections, or hospitalization when used on its own or in combination with hydroxyurea. Prolonged use of high doses of zidovudine has been associated with symptomatic myopathy (muscle damage). Rare but potentially fatal toxicity with all NRTIs is pancreatitis (inflammation of the pancreas), hepatomegaly (enlarged liver) with steatosis (fat) and lactic acidosis (accumulation of lactate in the blood and abnormal acid-base balance). Lactic acidosis has been seen in patients taking NRTIs but is more common and more severe in women, people who are obese, and people who have been taking nukes for a long time; and more common in people with liver disease, but can occur in people without a history of liver damage. People with lactic acidosis may experience persistent fatigue, abdominal pain or distension, nausea/vomiting, and difficulty breathing or shortness of breath; and enlarged, fatty liver. Pancreatitis can be life-threatening and may cause pain in the stomach and back, along with nausea, vomiting and blood in the urine. Risks for pancreatitis include: higher than recommended doses of NRTIs, advanced HIV, and alcohol use. The risk for pancreatitis with zidovudine is low compared to ddI.

POTENTIAL DRUG INTERACTIONS: Biaxin, Mycobutin, and rifampin (under various brand names) may decrease zidovudine blood levels. Benemid (probenecid), Dilantin (phenytoin), and Depakote (valproic acid) may increase zidovudine blood levels and decrease zidovudine clearance, but no dosing adjustments are recommended. Zidovudine and Zerit should not be used together due to evidence that one limits the other's effectiveness. Also, bone marrow supression should be monitored with use of Cytovene (ganciclovir), Valcyte, amphotericin B, pentamidine, dapsone, flucytosine, sulfadiazine, interferon-alpha, ribavirin (Rebetol), and with cancer treatments such as hydroxyurea and doxorubicin. Ribavirin and zidovudine may cancel each other out, so this combination should be monitored closely. New Procrit or Epogen warning: if hemoglobin target is above manufacturer's recommendation (12 g/dL), the risk for serious and life-threatening cardiovascular complications significantly increases. For zidovudine patients, measure hemoglobin once a week after starting the anemia drugs until hemoglobin has stabilized. Notify healthcare provider if experiencing pain and/or swelling in the legs, worsening in shortness of breath, increases in blood pressure, dizziness or loss of consciousness, extreme tiredness, or blood clots in hemodialysis vascular access ports. Do not take with Combivir or Trizivir, since zidovudine is already in these medications.

TIPS: In combination with Epivir, zidovudine is recommended as a preferred NRTI agent in U.S. HIV treatment guidelines in people on HIV therapy for the first time. The not-so-good news for people adding zidovudine: the fatigue and the potential anemia. You can start taking erythropoietin (Procrit or Epogen) for some anemias, but that's adding an expensive weekly injectable. Some doctors would prefer switching out the zidovudine for another drug. Also, some clinicians avoid the [illegible] drugs, or thymidine analogs (zidovudine and Zerit) because of implication in lipoatrophy. Zidovudine has for years been associated with "AZT butt," a disheartening flatness that happens gradually. Taking with food may minimize upset stomach. Please see package insert for more complete potential side effects and interactions.

Doctor

Retrovir, more commonly called AZT, was the first drug approved for the treatment of HIV infection, and it prolonged many lives back in the late [illegible] and early [illegible]. It got a new life in the form of Combivir after 3TC became available, experienced another resurrection as part of Trizivir, a once popular "triple-nuke" combination, and has been a cornerstone of therapy in the HAART era. However, AZT's time has finally passed. Compared to the nukes we're using now (namely tenofovir and abacavir), it's weaker, is dosed twice a day, is harder on the stomach, is more prone to resistance, and causes anemia and mitochondrial toxicity, including lipoatrophy. I still have a *few* patients still taking AZT because of resistance to other drugs (it becomes stronger if you have mutations that cause resistance to 3TC, FTC, abacavir, or tenofovir), but that may change as newer, safer agents become available. So long, AZT, and congratulations on a good, long run!– Joel Gallant, M.D.

Activist

Retrovir/AZT was the first drug developed for the treatment of HIV. In subsequent years, activists fought many battles to speed up the drug development process, but the history of AZT demonstrates that the mechanisms and ability to quickly test and approve drugs were present all along. What was lacking, except in the case of AZT, was the will to do it. AZT certainly has served a useful place in the history of treatment for HIV, but it has always come at a price. There is almost a cultural memory of the early and often severe side effects, but people don't always remember that this was primarily the result of overdosing. When dosed properly, AZT can still have side effects but they are seldom severe. Still, many people today believe it is time to reconsider the whole class of drugs that AZT comes from. Most of them have potentially significant side effects that derive from the very nature of what they are doing. It is difficult to conceive of a drug of this type that would be completely free of side effects. With so many new and relatively non-toxic drugs becoming available in recent years, it may be time to ask whether we can build fully effective regimens that don't rely on the old paradigm of "two nukes and a protease inhibitor" or "two nukes and a non-nuke." When this paradigm first became standard in 1996, it wasn't chosen because this was inherently the right or best way to treat HIV. Rather, it was simply the only kind of combination available at the time.–Martin Delaney

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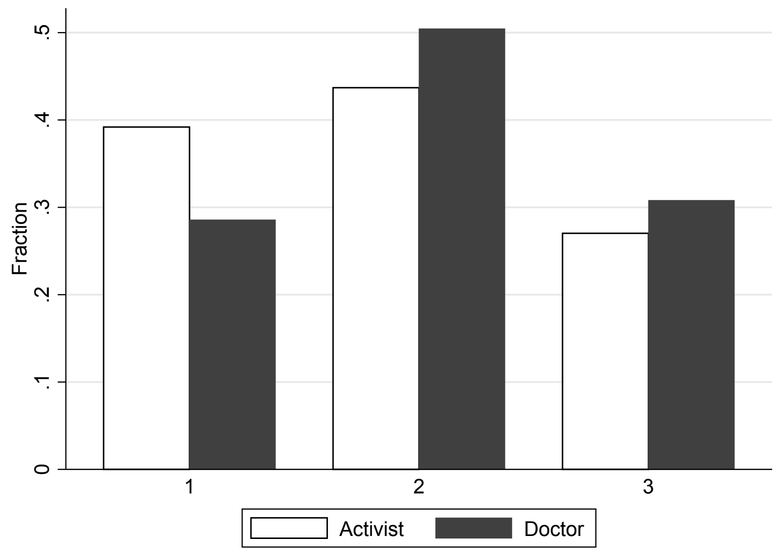
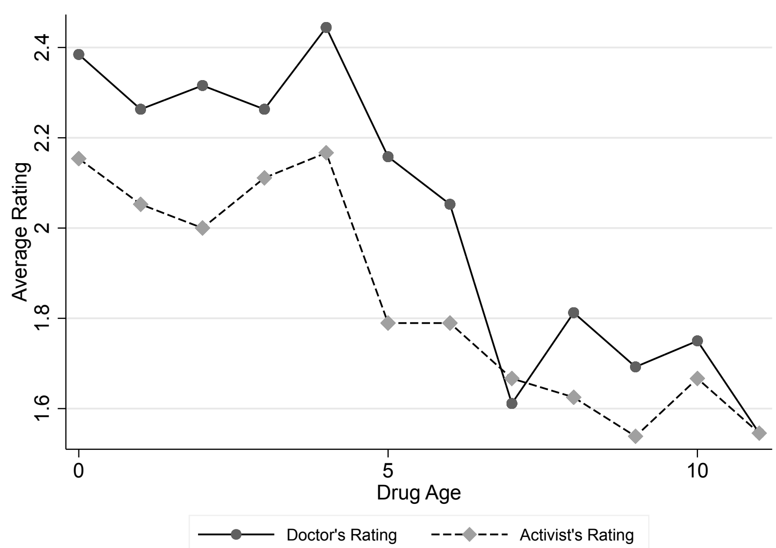
POSITIVELY AWARE

Figure C.1: SAMPLE PAGE FROM THE 2008 POSITIVELY AWARE DRUG GUIDE



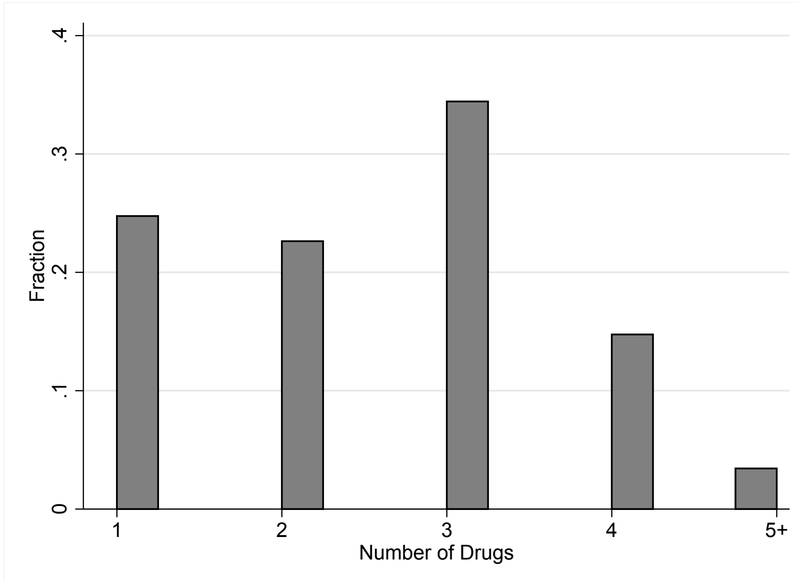
The Figure plots the fraction of 1's, 2's and 3's given to individual drugs, by expert.

Figure C.2: COMPARISON OF DOCTOR AND ACTIVIST RATINGS



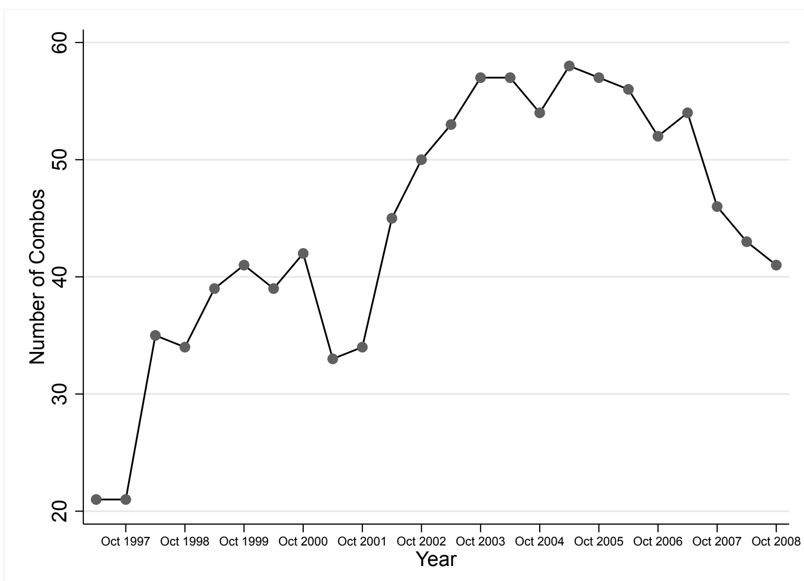
The Figure plots the average ratings of drugs over drug age, by expert.

Figure C.3: RATINGS OVER DRUG LIFE CYCLE



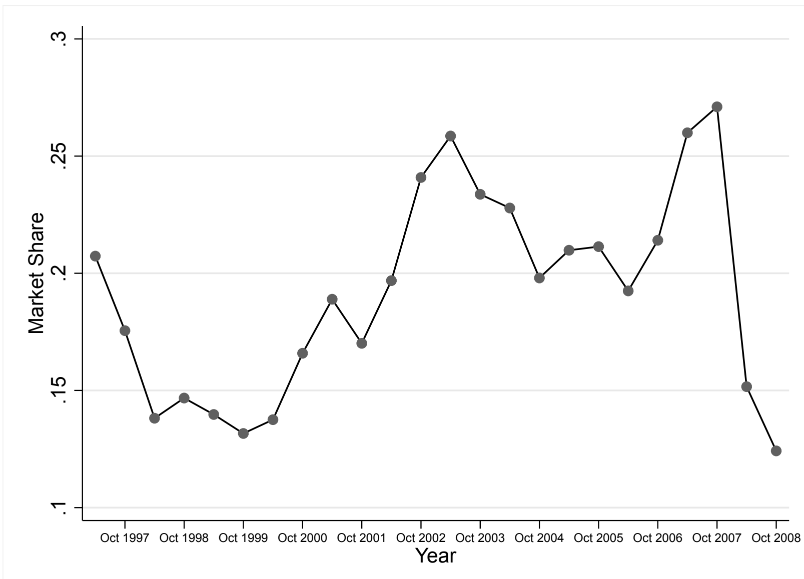
The Figure plots the distribution of drugs taken together in a combo.

Figure C.4: Distribution of Number of Drugs Taken Together



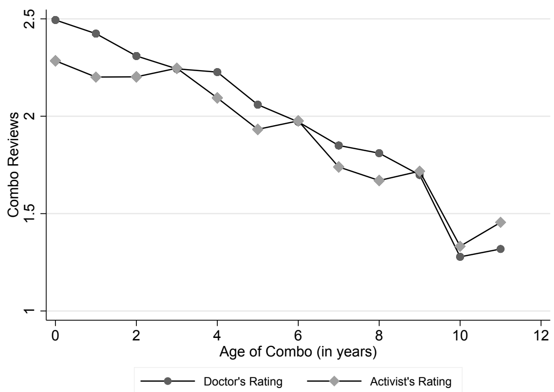
The Figure shows how the total number of combos (including 'Fringe') observed in the data evolves over the period of analysis.

Figure C.5: Total Number of Combos over Time

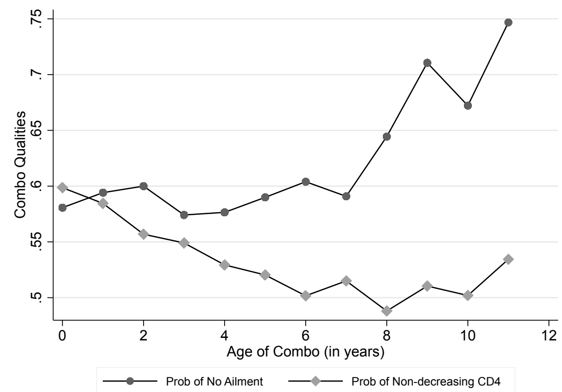


The Figure plots how the market share of the outside option, defined as taking no HIV treatment, evolves over the period of analysis.

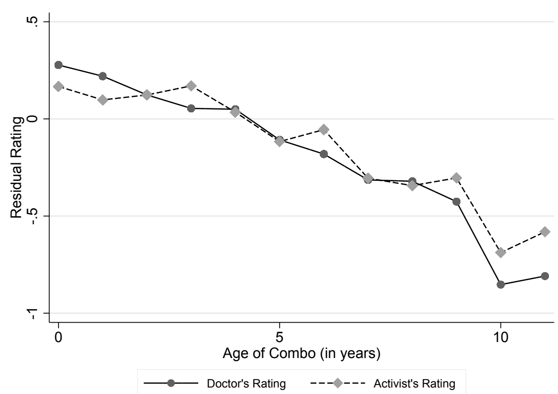
Figure C.6: Outside Option Market Share



(a) Ratings over Combo Age



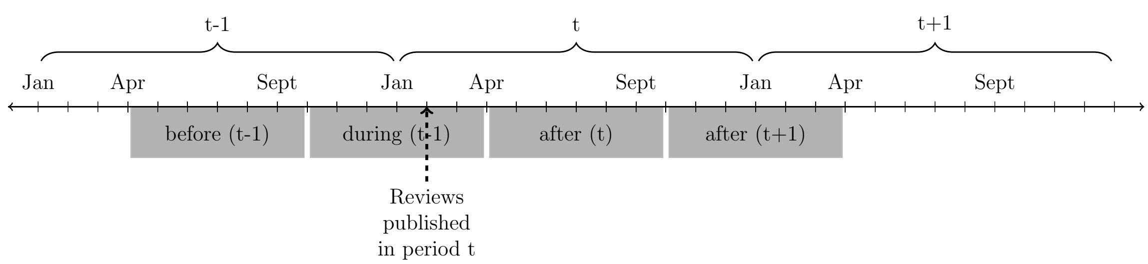
(b) Combo Qualities over Combo Age



(c) Residual Ratings over Combo Age

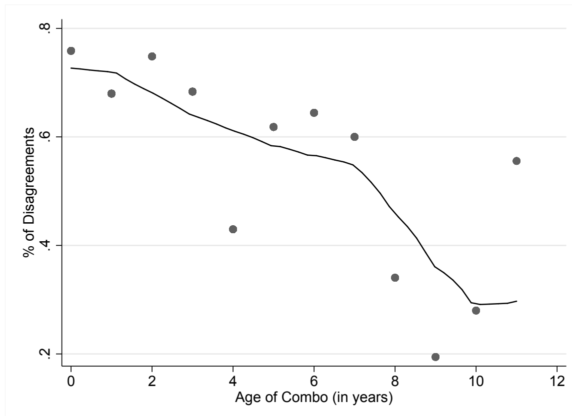
Figure C.7 (a) shows how the average combo ratings of the two experts evolves over the age of the combo. Figure C.7 (b) plots the evolution of objective qualities of combos, probability of no ailment and probability of no ailment, over combo age. Lastly, Figure C.7 (c) plots residual ratings for combo over combo age, where the residual ratings are the residual of an OLS regression of combo ratings on two objective qualities, probability of no ailment and probability of non-decreasing CD4 count.

Figure C.7: Combo Reviews and Qualities over the Life Cycle

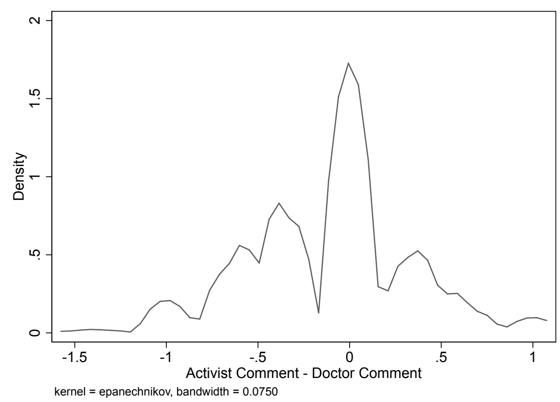


The Figure shows the timeline of events studied in the paper. Market share data is available for two six month windows, spanning from April to September and October to March. *PA* annual drug guides are published in January/February of every year, which coincides with the October-March window from the MACS data.

Figure C.8: Timeline of Events



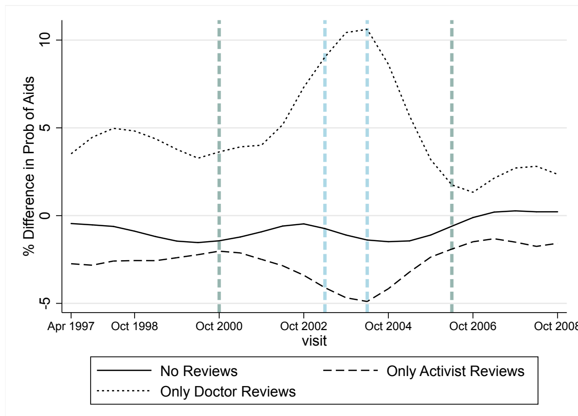
(a) Disagreement over Combo Age



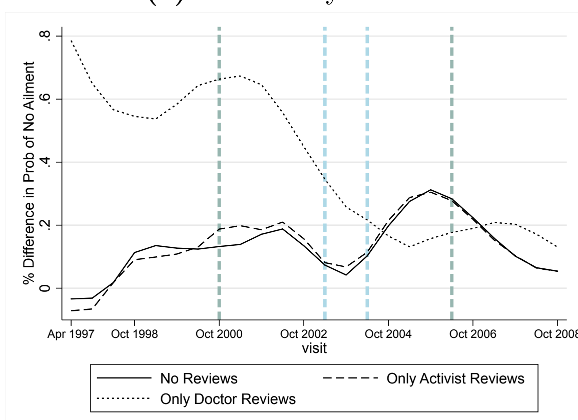
(b) Distribution of Differences

Figure C.9 (a) plots the percentage of disagreements between the doctor and activist about the rating of the combo over the age of the combo, where the variable disagreement is a dummy which is 1 if the activist and the doctor have a different rating for the combo. Figure C.9 (b) plots the distribution of the difference in combo ratings between the activist and the doctor.

Figure C.9: DISAGREEMENTS



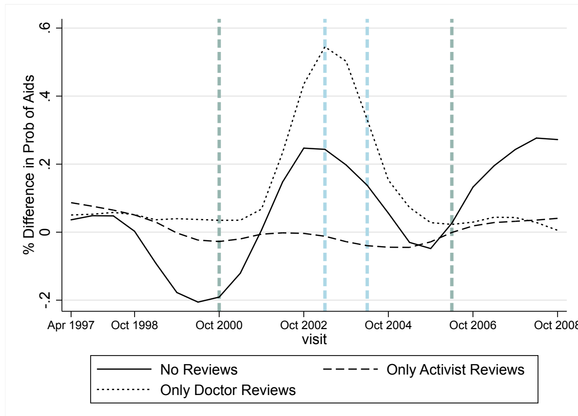
(a) Probability of Aids



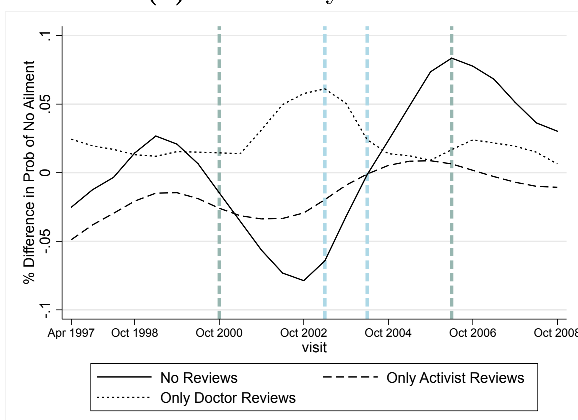
(b) Probability of No Ailment

Figure C.10 (a) plots the percentage difference in the probability of having AIDS in the next period from the baseline. The baseline is the scenario in which individuals have access to both reviews. Figure C.10 (b) plots the percentage difference in the probability of having no ailments in the next period from the baseline. The counterfactual scenarios considered are (1) having no reviews, (2) having only the activists' reviews, and (3) having only the doctors' reviews. The dotted vertical lines denote the introduction of new drugs onto the market.

Figure C.10: Average Difference in Health Outcomes - Full Sample



(a) Probability of Aids



(b) Probability of No Ailment

Figure C.11 (a) plots the percentage difference in the probability of having AIDS in the next period for individuals who have AIDS in the current period from the baseline. The baseline is the scenario in which individuals have access to both reviews. Figure C.11 (b) plots the percentage difference in the probability of having no ailments in the next period for individuals with AIDS in the current period from the baseline. The counterfactual scenarios considered are (1) having no reviews, (2) having only the activists' reviews, and (3) having only the doctors' reviews. The dotted vertical lines denote the introduction of new drugs onto the market.

Figure C.11: Average Difference in Health Outcomes - AIDS

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Curriculum Vitae

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